# Lógica Fuzzy e suas Aplicações

**Diálogos Ilum**

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# Um breve histórico da Lógica Fuzzy

- A lógica clássica se apoia em duas leis fundamentais:

  ● **Princípio do Terceiro Excluído**, que afirma que toda proposição deve ser verdadeira ou falsa e;

  ● **Princípio da não contradição**, que diz que nenhuma afirmação pode ser verdadeira e falsa simultaneamente.

- No século 19, George Boole criou um sistema de álgebra e teoria dos conjuntos para lidar matematicamente com essa lógica de dois valores (verdadeiro = 1 e falso = 0);

- Esses princípios levam a alguns paradoxos;

**Paradoxo do mentiroso:**

"Eu estou mentindo agora"

**Paradoxo do barbeiro/Paradoxo de Russel:**

"Considere uma cidade com apenas um barbeiro. Todos os homens da cidade se mantêm barbeados apenas de duas maneiras: ou barbeando-se ou indo ao barbeiro. Quem barbeia o barbeiro?"

# Um breve histórico da Lógica Fuzzy

- Bertrand Russell traz em sua obra (*Vagueness, 1923*) uma discussão sobre conceitos vagos e que a lógica clássica inevitavelmente leva à contradições.

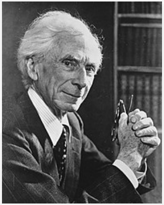


Figura: Bertrand Russell. Fonte: Wikipedia

" ... It is supposed that at first he was not bald, that he lost his hairs one by one, and that in the end he was bald; therefore, it is argued, there must have been one hair the loss of which converted him into a bald man. This, of course, is absurd. Baldness is a vague conception; some men are certainly bald, some are certainly not bald, while between them there are men of whom it is not true to say they must be either be bald or not bald. The law of excluded middle is true when precise symbols are employed, but it is not true when symbols are vague, as, in fact, all symbols are."

"Se a banana está amarela, então a banana está madura."

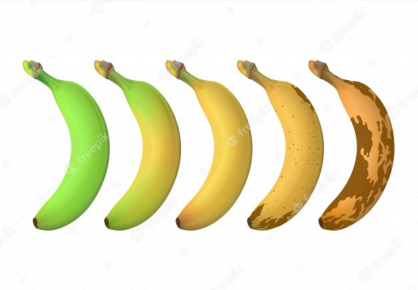


Figura: Escala de maturação da banana. Fonte: Freepik

# Um breve histórico da Lógica Fuzzy

- Jan Lukasiewicz propôs em sua obra (*O logice trójwartościowej, 1920*) uma lógica de três valores (verdadeiro = 1, possível = 0,5, falso = 0), que não teve ampla aceitação;

Figura: Jan Łukasiewicz. Fonte: Wikipedia

# Um breve histórico da Lógica Fuzzy

- Motivado por todos esses pensadores, Lotfi A. Zadeh publicou o artigo *"Fuzzy Sets", (1965)*, que tem hoje mais de 120 mil citações;

- Lotfi A. Zadeh nasceu em 4 de fevereiro de 1921 no Azerbaijão. Foi um matemático e engenheiro, professor da Universidade da Califórnia em Berkeley. Faleceu (6 de setembro de 2017) com 96 anos.

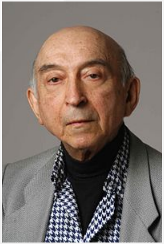


Figura: Lotfali Askar Zadeh. Fonte: Wikipedia

# Um breve histórico da Lógica Fuzzy

- Emigrou para o Irã para estudar na Universidade de Teerão e depois para os Estados Unidos em 1944, onde continuou os estudos no MIT;

- Recebeu diversas premiações pelas suas contribuições, dentre elas: Medalha Richard W. Hamming (1992), Medalha de Honra IEEE (1995) e Prêmio Richard E. Bellman (1998).


Figura: Lotfali Askar Zadeh. Fonte: Novayaepoxa

# Um breve histórico da Lógica Fuzzy

- De início os artigos de Zadeh não foram bem recebidos no ocidente;
- Ao longo do tempo a teoria foi ganhando seguidores principalmente no Japão, e em seguida na Coréia do Sul, China e India;
- A intenção de Zadeh era criar um formalismo para lidar com imprecisões do pensamento humano de forma mais eficiente;
- O princípio “fuzzy” estabelece que tudo é uma questão de grau de associação, variando de 0 (falso) a 1 (verdadeiro);
- Uma afirmação totalmente verdadeira seria por exemplo “Todas as pessoas são mortais”, uma vez que não há contra-exemplos para tal afirmação.

# Um breve histórico da Lógica Fuzzy

L. C. Barros e R. C. Bassanezi, (2021).

**Tópicos de lógica fuzzy e biomatemática**

*Universidade Estadual de Campinas (IMECC-UNICAMP)*

R. Belohlávek, J. W. Dauben and G. J. Klir, (2017).

**Fuzzy Logic and Mathematics: A Historical Perspective.**

*Oxford University Press, USA*

A. Garrido, (2012).

**A Brief History of Fuzzy Logic**

*BRAINotes*

Na literatura o termo “lógica fuzzy” é usado de duas formas diferentes:

- na teoria conjuntista, a fim de estender a teoria de conjuntos clássica;
- no sentido de “cálculo proposicional”, de modo a estender a lógica clássica.

A formulação matemática de incertezas via lógica fuzzy se diferencia da probabilidade.

Enquanto a estatística lida com incertezas antes dos eventos ocorrerem, a matemática fuzzy considera incertezas mesmo após o evento.

Por exemplo, no lançamento de uma moeda a probabilidade estima a “chance” de cara ou coroa, sendo que após o lançamento não há incerteza.


Figura: Fonte: Istockphoto

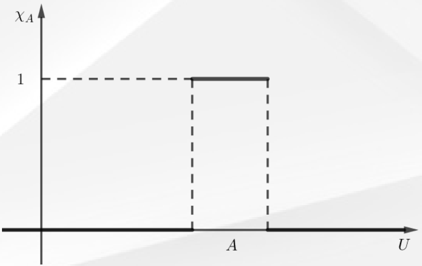
Enquanto a lógica fuzzy infere sobre o resultado, se as faces da moeda não são nítidas.

Figura: Fonte: Istockphoto

Dado um subconjunto $A$ de um universo $U$, a função característica de $A$, $\chi_A : U \to \{0,1\}$, é definida por

$$\chi_A(x) = \begin{cases} 1, se\ x \in A \\ 0, se\ x \notin A \end{cases}.$$

A função característica de um número real $a \in \mathbb{R}$ é dada por $\chi_{\{a\}}(x) = 1$, se $x = a$ ou $\chi_{\{a\}}(x) = 0$, se $x \neq a$.



Considere o conjunto $F$ dos números naturais pequenos:

$$F = \{n \in \mathbb{N} : \text{n é pequeno}\}.$$

Se a propriedade “pequeno” for precisamente definida, temos:

$$\chi_F(0) = \cdots = \chi_F(4) = 1 \quad \text{e} \quad \chi_F(5) = \chi_F(6) = \ldots = 0.$$

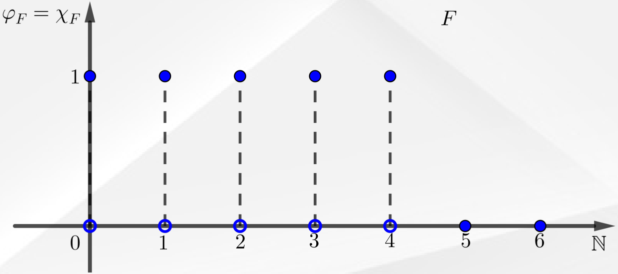



Figura: Representação gráfica do conjunto clássico $F = \{n \in \mathbb{N} : n \leq 4\}$.

## Definição de subconjunto fuzzy

Seja $U$ um conjunto universo. O subconjunto fuzzy $A$ de $U$ é caracterizado por sua função de pertinência $\varphi_A : U \to [0, 1]$.

A função de pertinência deve ser entendida da seguinte forma:

O valor $\varphi_A(x)$ em $[0, 1]$ é o grau de pertinência que o elemento $x$ está em $A$, de modo que sua pertinência a $A$ é tanto maior quanto maior for $\varphi_A(x)$.

No exemplo anterior a propriedade “pequeno” é precisamente definida. No entanto, dependendo da situação, não é razoável que 4 seja considerado “pequeno” enquanto 5 não.

Com intuito de fazer uma classificação com uma passagem não tão “brusca”, podemos adotar uma função (de pertinência) para descrever essa passagem de uma forma mais suave.

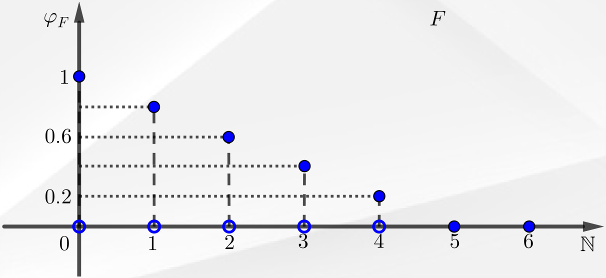
**Propriedade:** Se $x$ for pequeno e $y \leq x$, então $y$ também deve ser pequeno, ou seja, a função $\varphi_F$ deve ser decrescente.

Considere a seguinte função de pertinência:

$$\varphi_F(n) = \begin{cases} \frac{5-n}{5} & , \text{se } 0 \leq n \leq 4 \\ 0 & , \text{se } n > 4 \end{cases}. \tag{1}$$

Os números $0, 1, 2, 3, 4$ são considerados pequenos, mas com diferentes graus de pertinência.

$\varphi_F(0) = 1$, $\varphi_F(1) = 0,8$, $\varphi_F(2) = 0,6$, $\varphi_F(3) = 0,4$ e $\varphi_F(4) = 0,2$.



É razoável pensar que uma pessoa com um salário de 200 mil reais vive muito bem. Podemos talvez classificá-la como **rica**.

Por outro lado, não há dúvidas que uma pessoa com salário inferior a mil reais vive mal. Podemos classificá-la como **pobre**.

Estes casos representam situações opostas. Mas e uma pessoa que recebe 20 mil reais no Brasil? Podemos afirmar que esta pessoa vive bem! Mas podemos classificá-la como rica?

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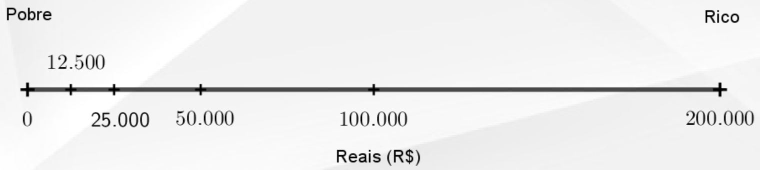
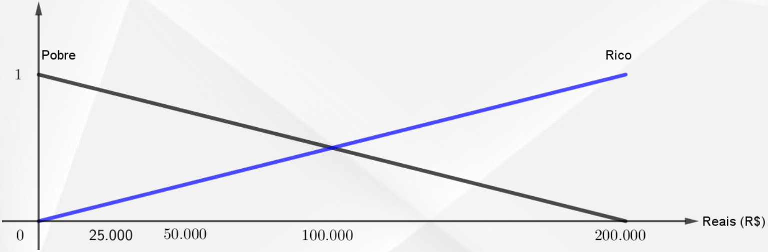
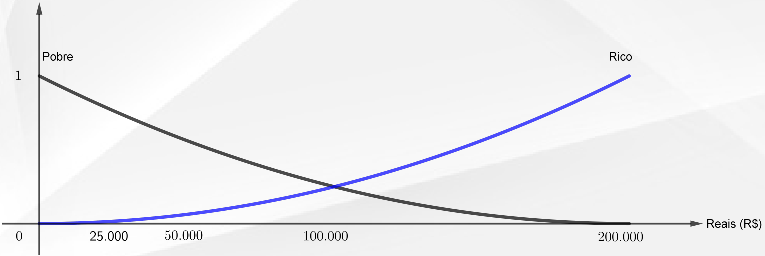
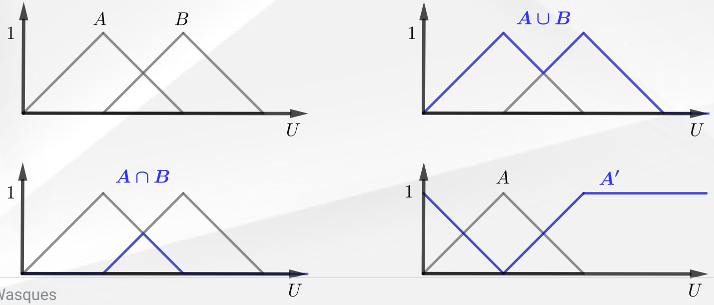


# Representação por conjuntos *fuzzy*



1. **União:** A união ($A \cup B$) entre conjuntos fuzzy é dada pela função de pertinência
$$\varphi_{A\cup B}(x) = \max\{\varphi_A(x), \varphi_B(x)\}, \forall x \in U$$
2. **Intersecção:** A intersecção ($A \cap B$) entre conjuntos fuzzy é dada pela função de pertinência
$$\varphi_{A\cap B}(x) = \min\{\varphi_A(x), \varphi_B(x)\}, \forall x \in U;$$
3. **Complemento:** O complementar ($A'$) de um conjunto fuzzy $A$ é dada pela função de pertinência
$$\varphi_{A'}(x) = 1 - \varphi_A(x), \forall x \in U.$$



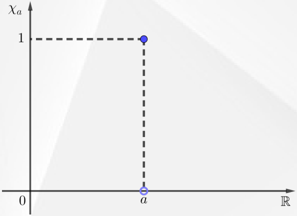



Figura: Número real (crisp).

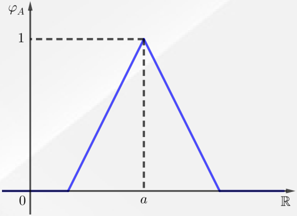



Figura: Número fuzzy (triangular)

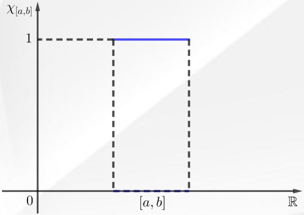



Figura: Intervalo real (crisp).

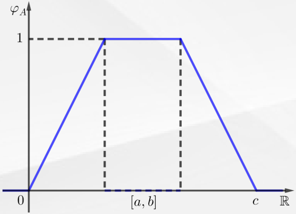
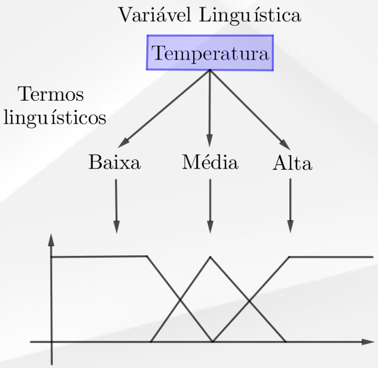



Figura: Número fuzzy (trapezoidal)

Uma **variável linguística** é uma variável cujo valor é:

- dado qualitativamente por termos linguísticos (que estabelece um adjetivo da variável);
- dado quantitativamente por uma função de pertinência (um conjunto fuzzy).



Um Sistema Baseado em Regras Fuzzy (SBRF), especificamente controladores fuzzy, é caracterizado por quatro componentes essenciais:

1. módulo de entrada (*fuzzificação*);
2. módulo de base de regras;
3. módulo de inferência fuzzy;
4. módulo de saída (*defuzzificação*).

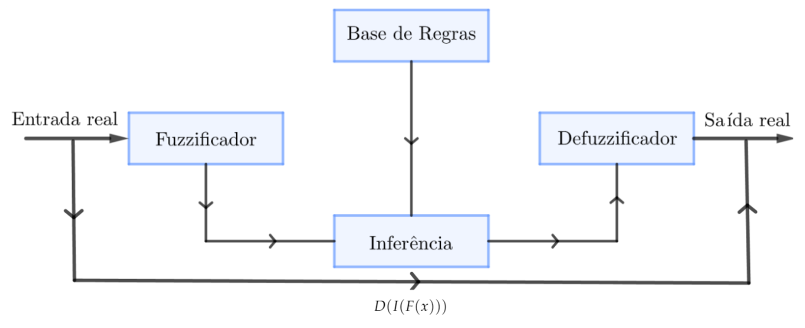



Figura: Diagrama de um SBRF. O símbolo $D(I(F(x)))$ é uma notação funcional do SBRF.

# Sistemas Baseado em Regras Fuzzy

- Módulo de fuzzificação: etapa em que as variáveis de entrada reais são "traduzidas" por conjuntos fuzzy;

- Regras fuzzy: são formadas por regras do tipo

  "Se *entrada*, então *saída*".

  As variáveis de *entrada* fazem parte do "domínio" e a *saída* do "contradomínio" do controlador.

- Método de inferência fuzzy são os métodos que permitem manipular cada entrada de modo a obter uma saída;

- Defuzzificação: constitui em representar um conjunto fuzzy através de um número real.

Em dinâmica de populações é aceito o princípio:

*"Em cada instante de tempo, a taxa de variação de uma população é diretamente proporcional a ela mesma"*

Malthus modelou essa lei pelo PVI

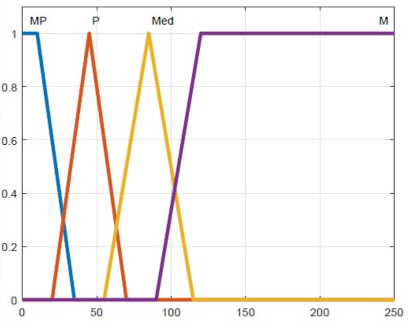
$$\begin{cases} \dfrac{dx}{dt} = \lambda x \\ x(t_0) = x_0 \in \mathbb{R} \end{cases}, \tag{2}$$

cuja solução é $x(t) = x_0 e^{\lambda t}$.

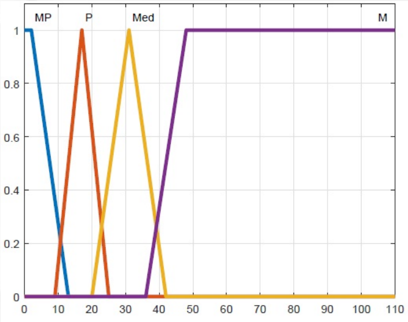
Agora a partir da lei é possível escrever a base de regras, considerando $t$ como entrada e variação $\frac{dx}{dt}$ como saída.

$$\begin{cases} R_1: \text{Se a população } x \text{ for } \textbf{muito pequena}, \text{ então a variação } \frac{dx}{dt} \text{ é } \textbf{muito pequena.} \\ R_2: \text{Se a população } x \text{ for } \textbf{pequena}, \text{ então a variação } \frac{dx}{dt} \text{ é } \textbf{pequena.} \\ R_3: \text{Se a população } x \text{ for } \textbf{média}, \text{ então a variação } \frac{dx}{dt} \text{ é } \textbf{média.} \\ R_4: \text{Se a população } x \text{ for } \textbf{grande}, \text{ então a variação } \frac{dx}{dt} \text{ é } \textbf{grande.} \end{cases}$$




(a) Conjuntos fuzzy para o antecedente população $x(t)$.




(b) Conjuntos fuzzy para o consequente taxa de variação $\frac{dx}{dt}$.

# Exemplo método de inferência de Mamdani:

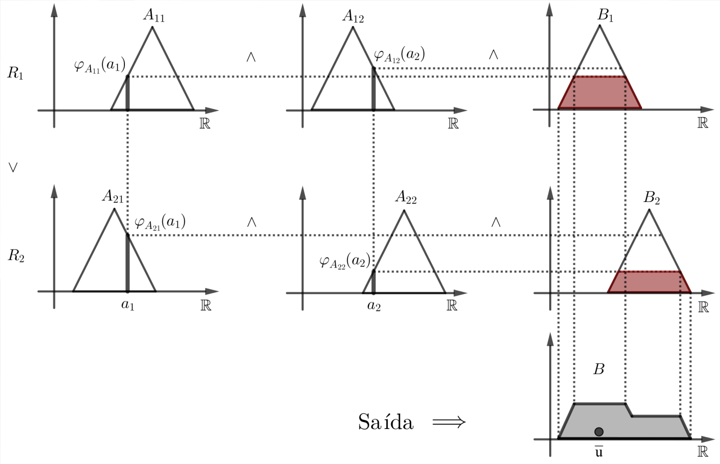



Figura: A região em cinza *B* representa a saída do sistema por Mamdani e $\overline{u} \in \mathbb{R}$ representa o valor defuzzificado de *B*.

A solução $x(t)$ do modelo é dada através do método clássico de Euler:

$$x_{n+1} = x_n + hSBRF_f(x_n),$$

em que $SBRF_f(x_n)$ representa a saída do SBRF, produzido pelo controlador fuzzy.

Por exemplo, se $h = 0,1$ e $x_0 = 2$, temos que $SBRF_f(x_0) \approx 4,1062$ e assim

$$x_1 = x_0 + h \cdot SBRF_f(X_0) = 2 + 0,1 \cdot 4,1062 \approx 2,4106,$$

e o processo de iteração continua de modo similar para $x_2, x_3, \ldots, x_n$.

# Modelo de Malthus

Com isso, a partir da base de regras dada anteriormente, obtem-se a seguinte solução dada na figura abaixo.

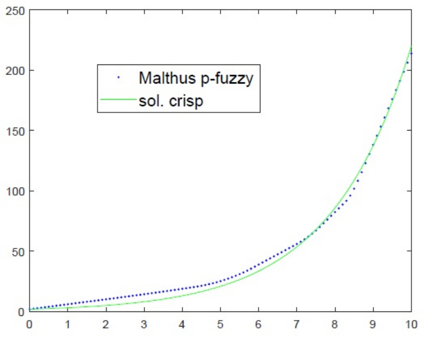



Figura: Soluções do modelo de Malthus via sistema p-fuzzy (linha pontilhada em azul) e via EDO (linha em verde). Os parâmetros utilizados foram $h = 0,1$, $x_0 = 2$ e $\lambda = 0,47$.

# Sistemas p-fuzzy

Esse método se baseia no uso de um sistema baseado em regras fuzzy e é chamado de p-fuzzy.

Esse tipo de abordagem estuda problemas em que o campo de direções de uma equação diferencial é conhecido apenas qualitativamente.

$$\begin{cases} \dfrac{dx}{dt} = f(x(t)) \\ x(t_0) = x_0 \in \mathbb{R} \end{cases},$$

sendo *f* descrito por uma base de regras fuzzy, consistente com o modelo a ser estudado.

# Modelo de Verhulst

O modelo de Verhulst tem como hipótese que, devido à limitação de recursos, há competição entre os indivíduos.

O modelo populacional discreto de Verhulst é descrito pela equação de diferenças logística

$$x_{n+1} = \lambda x_n \left(1 - x_n\right),$$

em que a variável $x_n$ é a densidade populacional da $n$-ésima geração.

Três situações:

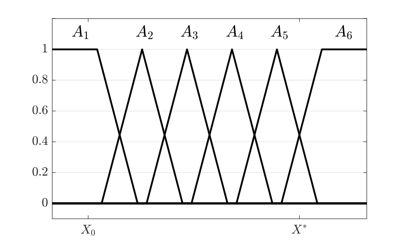
i) A sequência converge monotonicamente.

ii) A sequência converge, mas não monotonicamente.

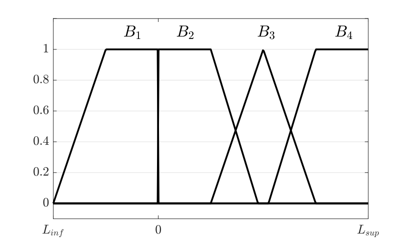
iii) A sequência assume um comportamento oscilatório.

Considerando $X$ como a variável de entrada e $\Delta X$ a de saída, temos a base de regras típica para modelo logístico.

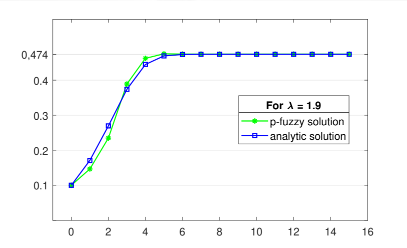
$r_1$ : Se $X$ é "*baixa*" ($A_1$), então a variação ($\Delta X$) é "*baixa positiva*" ($B_2$).
$r_2$ : Se $X$ é "*média baixa*" ($A_2$), então a variação ($\Delta X$) é "*média positiva*" ($B_3$).
$r_3$ : Se $X$ é "*média*" ($A_3$), então a variação ($\Delta X$) é "*alta positiva*" ($B_4$).
$r_4$ : Se $X$ é "*média alta*" ($A_4$) então a variação ($\Delta X$) é "*média positiva*" ($B_3$).
$r_5$ : Se $X$ é "*alta*" ($A_5$) então a variação ($\Delta X$) é "*baixa positiva*" ($B_2$).
$r_6$ : Se $X$ é "*muito alta*" ($A_6$) então a variação ($\Delta X$) é "*baixa negativa*" ($B_1$).



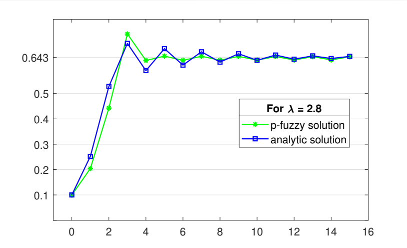

(a) Antecedentes da população $X$



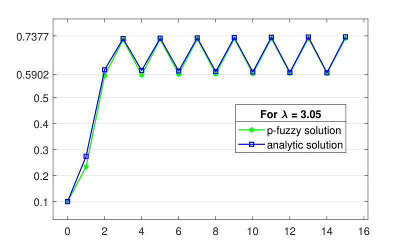

(b) Consequentes da variação $\Delta X$




(c) Caso convergência monotônica




(d) Caso convergência não monotônica




(e) Caso oscilatório de período 2

Derivada Fuzzy / Campo com incerteza

$$\begin{cases} y'_{\mathcal{J}}(x) = f(y(x), x) \\ y(x_0) = y_0 \in \mathbb{R}_{\mathcal{F}} \end{cases}$$

**Abordagens:**

- Utilizar conceitos de derivadas e integrais fuzzy;
- Estender métodos numéricos clássicos;
- Associar o PVIF com um sistema de EDOs.

Condição inicial/fronteira Fuzzy

$$\begin{cases} y'(x) = f(y(x), x) \\ y(x_0) = y_0 \in \mathbb{R}_{\mathcal{F}} \end{cases} .$$

**Abordagens:**

- Utilizar princípios de extensões fuzzy;
- Estender métodos numéricos clássicos.

Considere o modelo de decaimento malthusiano

$$\begin{cases} X'(t) & = & -\lambda X(t) \\ X(0) & = & A \in \mathbb{R}_{\mathcal{F}} \end{cases}, \qquad (3)$$

sendo $\lambda > 0$.

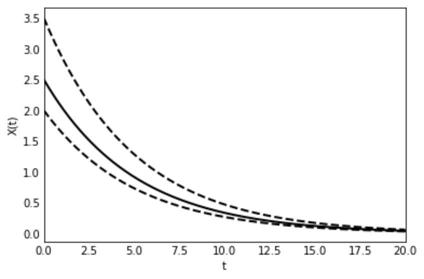
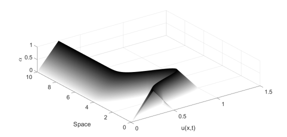


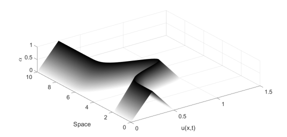

Figura: Solução fuzzy obtida pelo sistema (3) associada a derivada fuzzy (correlacionada). Fonte: Barros, L.C. *et al.* Cálculo para Processos Fuzzy Interativos

A equação de advecção é dada por

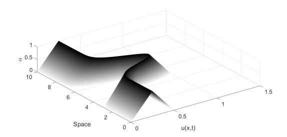
$$\begin{cases} u_t + \kappa u_x = 0 \\ u(x,0) = \eta(x) \in \mathbb{R}_{\mathcal{F}} \end{cases} \tag{4}$$



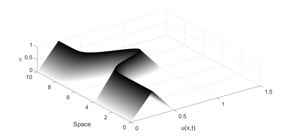

(a) Solução fuzzy em $t_0$.




(b) Solução fuzzy em $t_1$.




(c) Solução fuzzy em $t_2$.




(d) Solução fuzzy em $t_3$.

Figura: Fonte: Wasques, V. F. *et al.* Solution to the Advection Equation with Fuzzy Initial Condition via Sup-J Extension Principle

# Aplicações - Cálculo fuzzy

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## Fuzzy differential equations with interactive derivative

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Received 3 December 2014; received in revised form 1 April 2016; accepted 6 April 2016
Available online 12 April 2016

**Abstract**

In this paper we introduce and study new concept of differentiability for fuzzy-set-valued functions. This derivative considers possible local interactivity in the process studied. Several properties of differentiability and integrability are investigated for the new concept and they are compared to similar fuzzy differentiabilities like Hukuhara differentiability and generalized Hukuhara differentiability. Furthermore, we establish theorems as the fundamental theorem of calculus. Ultimately, we exhibit some results for fuzzy initial value problem and an application.


*Keywords:* Analysis; Fuzzy-set-valued function; Interactive fuzzy process; Fuzzy derivative; Fuzzy differential equation

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## The generalized fuzzy derivative is interactive

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A B S T R A C T

In this article, we prove that the generalized difference between $A, B \in \mathbb{R}_{\mathcal{F}_C}$, i.e., fuzzy numbers with continuous endpoints, is given by an interactive difference. To be more precise, we construct a certain joint possibility distribution $J$ such that the generalized difference coincides with the sup-$J$ extension of the subtraction. As an immediate consequence, we have that every notion of difference between $A, B \in \mathbb{R}_{\mathcal{F}_C}$, that has so far appeared in the literature, can be derived from a sup-$J$ extension for some particular choice of $J$. Moreover, we show that both the generalized and the generalized Hukuhara derivative of a function $f : \mathbb{R} \to \mathbb{R}_{\mathcal{F}_C}$ at $x \in \mathbb{R}$ can be expressed as the limit for $h \to 0$ of a difference quotient, where the difference is an interactive difference for each $h$. For short, we say that the generalized (as well as the generalized Hukuhara) difference is interactive.



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## Solutions of higher order linear fuzzy differential equations with interactive fuzzy values

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**Abstract**

In this study, we consider higher order linear differential equations with additional conditions (initial and/or boundary) given by interactive fuzzy numbers. The concept of interactivity arises from the notion of a joint possibility distribution (J). The proposed method for solving fuzzy differential equations is based on an extension of the classical solution via sup-$J$ extension, which is a generalization of Zadeh's extension principle. We prove that under certain conditions, the solution via Zadeh's extension principle is equal to the convex hull of the solutions produced by the sup-$J$ extension. We also show that the solutions based on the Fréchet derivatives of fuzzy functions coincide with the solutions obtained via the sup-$J$ extension. All of the results are illustrated based on a 3rd order fuzzy boundary value problem.


*Keywords:* Interactive fuzzy numbers; Sup-$J$ extension principle; Fréchet derivative; Fuzzy differential equations

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## Calculus for linearly correlated fuzzy function using Fréchet derivative and Riemann integral

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A B S T R A C T

In this manuscript we study integration and derivative theories for interactive fuzzy processes. These theories are based on the Fréchet derivative and the Riemann integral. In addition, we present a connection between these two theories, i.e., some problems may be formulated in both ways. We establish the fundamental theorem of calculus, theorem of existence and the local uniqueness of the solution of fuzzy differential equations and some techniques to solve fuzzy initial value problems. To illustrate the usefulness of the developed theory, we investigate the radioactive decay model.

# Aplicações - Biomatemática fuzzy

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## Population growth model via interactive fuzzy differential equation

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Logistic model

A B S T R A C T

In this manuscript we study a fuzzy initial value problem (FIVP) which describes an autocorrelated evolutive process. For this, we use the $\mathcal{F}$-correlated derivative ($\mathcal{F}$-derivative) concept on fuzzy-number-valued functions. This approach lets us establish a relationship between the diameter of the FIVP solution and its derivative. Moreover, we notice how the derivative influences the interactivity of the process by computing the measure of possibilistic interactivity of the FIVP solution. We analyze a population growth model, namely, the Logistic model, with our approach and compare the results with another approach that uses the generalized derivative of Hukuhara (gH-derivative). Finally, we conclude that in fuzzy differential equations describing locally $\mathcal{F}$-correlated fuzzy processes, the use of the interactive derivative is more adequate than the gH-derivative for a fuzzy number-valued function.



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Research Article

## Numerical Solution for Fuzzy Initial Value Problems via Interactive Arithmetic: Application to Chemical Reactions

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**ABSTRACT**

This paper studies numerical solutions for fuzzy initial value problems, where the initial conditions are given by interactive fuzzy numbers. The fuzzy solution is given by a numerical method that employs the arithmetic of interactive fuzzy numbers and yields a fuzzy number at each instant of time. The computational cost of the numerical method is also provided. The chemical decay reaction model is considered in order to illustrate that different types of interactivity produce different solutions for initial value problems. In addition, we present an application to the Lotka–Volterra model of oscillating chemical reactions.



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## Modelo de competição de Gause com esforço de pesca e fatores abióticos

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Bolsista Fapeam - Universidade Federal do Amazonas

Rodney C. Bassanezi[2],
DMA, IMECC, Unicamp 13.083-859, Campinas/SP.

**Resumo** Várias espécies de peixes consumidas na região Amazônica interagem entre si por meio de competição, neste trabalho estudamos o modelo clássico de competição de Gause inserindo esforço de pesca e fatores abióticos para analisar o comportamento dos níveis de estoque de peixes das populações. Além disso, devido as incertezas inerentes as condições iniciais e também ao esforço de pesca aplicado, realizamos um estudo fuzzy desse modelo.

***Palavras-chave****: Lógica fuzzy; fator abiótico; esforço de pesca.*

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## Periodicidade em dinâmica populacional com incertezas

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Diego F. Gomes[2],
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**Resumo**. Neste trabalho analisamos os efeitos provocados pela inserção de parâmetros periódicos em modelos de dinâmica populacional de uma espécie, onde a condição inicial é considerada incerta. Mais especificamente, usamos um sistema dinâmico fuzzy (condição inicial fuzzy), associado a um modelo inibido com coeficientes periódicos. Neste contexto obtemos um teorema de existência e unicidade da solução fuzzy. A motivação deste é trabalho é proveniente da modelagem da dinâmica populacional do *Donax gemmula*.

***Palavras-chave****: Biomatemática; Donax gemmula; Sistemas dinâmicos fuzzy; Periodização.*

# Aplicações - Biomatemática fuzzy

*Biomatemática* **28** *(2018), 25–38* **ISSN 1679-365X**
*Uma Publicação do Grupo de Biomatemática IMECC – UNICAMP*

## Modelagem fuzzy para predizer riscos de metástase e morte para neoplasia de rim

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**Resumo**. As neoplasias renais malignas têm importante significado clínico e são responsáveis por cerca de 2% dos tumores malignos em humanos, sendo mais frequentes os carcinomas de células renais (CCR). A discussão e compreensão dos fatores prognósticos do CCR são fundamentais para estabelecer-se uma abordagem na condução desses tumores. O propósito desse artigo é mostrar aplicações da Teoria de Conjuntos Fuzzy, para predizer o risco de desenvolvimento de metástase e o risco de morte em pacientes que apresentam tumor de rim com o subtipo mais comum, conhecido como convencional (células claras). A intenção foi analisar a relação entre determinados fatores prognósticos (principalmente a graduação de Fuhrman) e a sobrevida dos pacientes. A Classificação de Fuhrman é conhecida mundialmente e consiste num sistema de graduação do câncer renal, feito a partir da diferenciação do núcleo celular de uma célula cancerosa, ao compará-la com uma sadia. Este trabalho foi motivado pelo fato de que médicos especialistas vêm constatando em casos reais, pacientes com graus de Fuhrman baixos (considerados satisfatórios) e que apresentam um prognóstico desfavorável. O primeiro modelo matemático fuzzy desenvolvido, cuja saída é o "risco de metástase", combina os dados pré-cirúrgicos dos pacientes - grau de Fuhrman, estadiamento, presença de necrose e tamanho do tumor. Já o segundo modelo fuzzy construído tem como

*Biomatemática* **18** *(2008), 27–36* **ISSN 1679-365X**
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## Software desenvolvido a partir de um Modelo Matemático *Fuzzy* para predizer o estágio patológico do Câncer de Próstata

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Laércio L. Vendite[2], Laécio C. Barros[3]
DMA, IMECC – UNICAMP, 13.083-859, Campinas/SP.

**Resumo**. Nosso trabalho propõe um modelo matemático fuzzy para predizer o estágio patológico do câncer de próstata (Silveira, 2007). O modelo consiste num sistema baseado em regras fuzzy, que combina os dados pré-cirúrgicos do paciente - estado clínico, nível de PSA e grau de Gleason - valendo-se de regras lingüísticas, elaboradas a partir dos nomogramas já existentes. Com isso esperava-se obter a chance de o indivíduo estar em cada estágio de extensão do tumor: localizado, localmente avançado e metastático. Foram feitas simulações com dados reais de pacientes do Hospital das Clínicas da UNICAMP e os resultados foram comparados com as probabilidades de Kattan (Stephenson e Kattan, 2006). Um software foi desenvolvido a partir deste modelo e será disponibilizado aos especialistas do mesmo hospital. O programa escrito em **JAVA** consiste em uma interface gráfica que faz a interação com as sub-rotinas que efetuam os cálculos.

***Palavras-chave:*** *Câncer de Próstata, Modelo Matemático, Lógica Fuzzy, Software, Biomatemática.*

## SBRF com Aplicações em Classificação de Risco de Endometriose

Daniel Dias de Carvalho Santos, Jorge Féres Junior, Nilmara de Jesus Biscaia Pinto, Renato Lopes Moura, Kleber Cursino de Andrade, Estevão Esmi Laureano e Peter Sussner

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**Resumo.** Neste trabalho será analisada a aplicação de um sistema de base de regras fuzzy no problema de classificação de risco de endometriose utilizando o método clássico de inferência de Mamdani. Simulações computacionais serão conduzidas a fim de avaliar a qualidade da base de regras proposta.

**Palavras-chave:** Endometriose; classificação de risco; inferência fuzzy; sistema de base de regras fuzzy.

# Aplicações - Biomatemática fuzzy

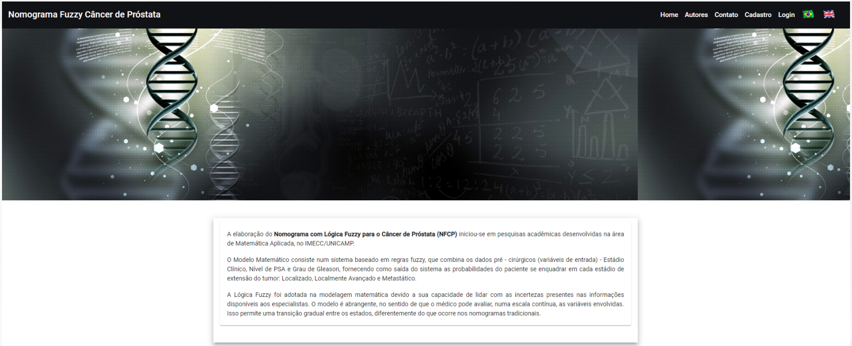


Figura: Para acessar a plataforma do Nomograma Fuzzy, clique aqui ilum

## Carbon Emissions Trading as a Constraint in a Fuzzy Optimization Problem

Nilmara de Jesus Biscaia Pinto, Estevão Esmi and Laécio Carvalho de Barros

**Abstract** This work presents some climate changing policies and intends to model carbon emissions trading as a constraint in a fuzzy optimization problem. Bellman-Zadeh decision scheme is used within Zimmermann approach in order to estimate the gain in carbon markets notwithstanding to lost in entities welfare function, seen as the objective function.

**Key words:** Fuzzy Optimization Problem, Climate Changing, Carbon Emissions Trading

### 1 Introduction

Climate change is nowadays one of the most studies subject and the cause of amount of international negotiations [13]. Kyoto protocol (1995), signed by 192 parties, is one result from these arrangements. This pact created the Emissions Trading Systems (ETS), which converts greenhouse gas emissions in a new commodity: a mean to facility countries to reach the target of reducing greenhouse gas emissions [16].

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## Fuzzy Global Optimization of Complex System Reliability

V. Ravi, P. J. Reddy, and Hans-Jürgen Zimmermann

***Abstract*—In this paper, the problem of optimizing the reliability of complex systems has been modeled as a fuzzy multi-objective optimization problem where apart from the system reliability, system cost, weight, and volume are all considered as fuzzy goals/objectives. Three different kinds of optimization problems: 1) reliability optimization of a complex system with constraints on cost and weight; 2) optimal redundancy allocation in a multistage mixed system with constraints on cost and weight; and 3) optimal reliability allocation in a multistage mixed system with constraints on cost, weight, and volume have been solved. Four numerical examples have been solved to demonstrate the effectiveness of the present methodology. The influence of various kinds of aggregators such as: 1) *product* operator; 2) *min* operator; 3) the *arithmetic mean* operator; 4) fuzzy *and* 5) a convex combination of the *min* and the *max* operators; and 6) compensatory and ($\gamma$-operator) on the quality of the solutions is also studied. The inefficiency of the noncompensatory *min* operator has been demonstrated. One of the well-known global optimization meta-heuristics—threshold accepting—has been invoked to take care of the optimization part of the model because it is a variant of the simulated annealing algorithm and, hence, can tackle the nonconvex optimization problems very well, unlike the modified steepest-ascent method [6], [8]. Linear membership functions have been assumed for the all the goals/objectives. A software has been developed to implement the above model. The results are encouraging because in the case of some problems investigated here they coincided with those yielded in the crisp single-objective environment. Also, fuzzy optimization techniques can be used as viable and useful alternatives to the goal programming approaches for this kind of problems posed in an ill-structured environment.**

***Index Terms*—Complex systems, multi-objective optimization, optimal redundancy allocation, Pareto optimal solution, reliability, fuzzy optimization, threshold accepting algorithm.**

2) *Probability assumption:* the system failure behavior is fully characterized by the probability measures.

Although, these two assumptions are often valid, they are not reasonable in a large variety of cases. This called for the incorporation of the concepts of fuzzy set theory into these assumptions. Thus, 1) and 2) are modified as follows [1].

1′) *Fuzzy state assumption:* the system success and failure are characterized by fuzzy states. At any given time the system can be viewed as being in one of the two states to some extent. Thus, system failure is not defined in a binary way, but in a fuzzy way.

2′) *Possibility assumption:* the system failure behavior is fully characterized by the possibility measures.

For the sake of simplicity, the conventional reliability theory is called "PROBIST reliability theory," since it is based on assumptions 1) and 2). When 1) is replaced by 1′) and/or 2) is replaced by 2′), the resultant is called fuzzy reliability theory. Thus fuzzy reliability theory manifests itself in three different forms viz. PROFUST reliability theory, POSBIST reliability theory, and POSFUST reliability theory [1].

Fuzzy reliability theory in its various forms found applications, especially in fault tree analysis [2], [3], reliability optimization [4] and risk analysis [5]. However, fuzzy mathematical techniques can be successfully applied to conventional reliability theory, without taking recourse to any form of the fuzzy reliability theories. This was first demonstrated by Park [6], who applied fuzzy optimization techniques to the problem of reliability apportionment for a simple two-component series

## Least Squares Method with Interactive Fuzzy Coefficient: Application on Longitudinal Data

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**Abstract.** This work focus on the least square method to fit a fuzzy function to longitudinal data given by fuzzy numbers. In order to consider the intrinsic correlation of longitudinal data, we assume that there exits a linear relation among the involved fuzzy numbers that arises from the concept of a joint possibility distribution. We propose a numerical method to solve a fuzzy least square problem taking into account this linear correlation. To this end, we extend the classical least square method by means of the sup-$J$ extension principle, which consists of a generalization of Zadeh's extension principle. Finally, we use our proposal method to fit a longitudinal dataset.

**Keywords:** Fuzzy least square method · Interactive fuzzy numbers Joint possibility distribution · Longitudinal data

## Least Square Method with Quasi Linearly Interactive Fuzzy Data: Fitting an HIV Dataset

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**Abstract.** In this manuscript we propose a method to fit a dataset with uncertainty. These data are described by interactive fuzzy numbers. The relationship of interactivity is associated with the notion of joint possibility distribution. We focus on a specific type of interactivity namely linear interactivity. We use this concept to introduce a class of fuzzy numbers called quasi linearly interactive fuzzy numbers. We provide an application to fit a dataset of the HIV disease to illustrate the proposed method.

# Aplicações - Redes neurais fuzzy

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## Uninorm based evolving neural networks and approximation capabilities

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ABSTRACT

Learning from data streams is a contemporary and demanding issue because of the constantly increasing rate in size and temporal availability of data, turning traditional learning methods impracticable. This work suggests a structure and introduces a learning approach to train uninorm-based hybrid neural networks using extreme learning concepts. Uninorms bring flexibility and generality to fuzzy neuron models as they can benefit from triangular norms, triangular conorms, or operations in between by adjusting identity elements. This feature adds a form of plasticity in neural network modeling. Fuzzy c-means are used to granulate the input space, and a scheme based on extreme learning is employed to compute the weights of the neural network. We show that the network approximates any continuous functions in compact domains. Subsequently, an evolving version of the network is developed exploring recursive clustering methods and extreme learning. It is postulated, and computational experiments endorse, that the evolving neuro fuzzy network shares equal or better approximation ability in dynamic environments than its static counterpart.



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Neural Networks

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## Evolving granular neural networks from fuzzy data streams

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ABSTRACT

This paper introduces a granular neural network framework for evolving fuzzy system modeling from fuzzy data streams. The evolving granular neural network (eGNN) is able to handle gradual and abrupt parameter changes typical of nonstationary (online) environments. eGNN builds interpretable multi-sized local models using fuzzy neurons for information fusion. An online incremental learning algorithm develops the neural network structure from the information contained in data streams. We focus on trapezoidal fuzzy intervals and objects with trapezoidal membership function representation. More precisely, the framework considers triangular, interval, and numeric types of data to construct granular fuzzy models as particular arrangements of trapezoids. Application examples in classification and function approximation in material and biomedical engineering are used to evaluate and illustrate the neural network usefulness. Simulation results suggest that the eGNN fuzzy modeling approach can handle fuzzy data successfully and outperforms alternative state-of-the-art approaches in terms of accuracy, transparency and compactness.



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## Evolving fuzzy and neuro-fuzzy approaches in clustering, regression, identification, and classification: A Survey

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ABSTRACT

Major assumptions in computational intelligence and machine learning consist of the availability of a historical dataset for model development, and that the resulting model will, to some extent, handle similar instances during its online operation. However, in many real-world applications, these assumptions may not hold as the amount of previously available data may be insufficient to represent the underlying system, and the environment and the system may change over time. As the amount of data increases, it is no longer feasible to process data efficiently using iterative algorithms, which typically require multiple passes over the same portions of data. Evolving modeling from data streams has emerged as a framework to address these issues properly by self-adaptation, single-pass learning steps and evolution as well as contraction of model components on demand and on the fly. This survey focuses on evolving fuzzy rule-based models and neuro-fuzzy networks for clustering, classification and regression and system identification in online, real-time environments where learning and model development should be performed incrementally.



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## Evolving Granular Fuzzy Model-Based Control of Nonlinear Dynamic Systems

Daniel Leite, *Member, IEEE*, Reinaldo M. Palhares, Victor C. S. Campos, and Fernando Gomide, *Senior Member, IEEE*

***Abstract*—Unknown nonstationary processes require modeling and control design to be done in real time using streams of data collected from the process. The purpose is to stabilize the closed-loop system under changes of the operating conditions and process parameters. This paper introduces a model-based evolving granular fuzzy control approach as a step toward the development of a general framework for online modeling and control of unknown nonstationary processes with no human intervention. An incremental learning algorithm is introduced to develop and adapt the structure and parameters of the process model and controller based on information extracted from uncertain data streams. State feedback control laws and closed-loop stability are obtained from the solution of relaxed linear matrix inequalities derived from a fuzzy Lyapunov function. Bounded control inputs are also taken into account in the control system design. We explain the role of fuzzy granular data and the use of parallel distributed compensation. Fuzzy granular computation provides a way to handle data uncertainty and facilitates incorporation of domain knowledge. Although the evolving granular approach is oriented to control systems whose dynamics is complex and unknown, for expositional clarity, we consider online modeling and stabilization of the well-known Lorenz chaos as an illustrative example.**

***Index Terms*—Dynamic systems, evolving systems, fuzzy control, fuzzy modeling, granular computation.**

Robust control [4] has long been recognized as a general and effective control approach provided that bounds on the uncertainty of the process parameters are known, and fairly accurate knowledge about the structure of the process model is available. There is no evidence, however, that a robust control system designed offline will perform properly if the process or the surrounding environment changes, especially if the uncertainty tolerance range is small [5], [6]. Among the reasons for the changes are aging, wearing, operation mode variation, faults, and seasonality [7]. A persuasive mechanism to deal with time-varying dynamics in modeling and control problems is adaptation.

Adaptive control consists of an array of techniques for automatic adjustment of controllers to achieve and keep a desired performance, even if the process parameters change over time [2]. Adaptation is performed based on input–output data collected from the process. Although the indirect method for adaptive control [8], [9] is well developed for linear models and controllers, it is not for the case of nonlinear, nonstationary, and uncertain systems [5]. Moreover, adaptive control usually assumes fixed model and controller structure and is mainly applied to parameters. When the process is subject to abrupt and

# Aplicações - Redes neurais fuzzy

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Energy

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## Short-term load forecasting by using a combined method of convolutional neural networks and fuzzy time series

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A B S T R A C T

We propose a combined method that is based on the fuzzy time series (FTS) and convolutional neural networks (CNN) for short-term load forecasting (STLF). Accordingly, in the proposed method, multivariate time series data which include hourly load data, hourly temperature time series and fuzzified version of load time series, was converted into multi-channel images to be fed to a proposed deep learning CNN model with proper architecture. By using images which have been created from the sequenced values of multivariate time series, the proposed CNN model could determine and extract related important parameters, in an implicit and automatic way, without any need for human interaction and expert knowledge, and all by itself. By following this strategy, it was shown how employing the proposed method is easier than some traditional STLF models. Therefore it could be seen as one of the big difference between the proposed method and some state-of-the-art methodologies of STLF. Moreover, using fuzzy logic had great contribution to control over-fitting by expressing one dimension of time series by a fuzzy space, in a spectrum, and a shadow instead of presenting it with exact numbers. Various experiments on test data-sets support the efficiency of the proposed method.



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Applied Energy

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## Time-series prediction of wind speed using machine learning algorithms: A case study Osorio wind farm, Brazil

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H I G H L I G H T S

- Machine learning algorithms are developed to predict the time-series wind speed data.
- The developed models are MLFFNN, SVR, FIS, ANFIS, ANFIS-PSO, ANFIS-GA and GMDH.
- The employed models were examined on 5-min, 10-min, 15-min and 30-min intervals.
- GMDH model for all time intervals can successfully predict the target.
- PSO and GA algorithms can increase the prediction accuracy of the ANFIS model.

A R T I C L E I N F O

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Neural networks
Adaptive neuro-fuzzy inference system
Group method of data handling
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Genetic algorithm

A B S T R A C T

Machine learning algorithms (MLAs) are applied to predict wind speed data for Osorio wind farm that is located in the south of Brazil, near the Osorio city. Forecasting wind speed in wind farm regions is valuable in order to obtain an intelligent management of the generated power and to promote the utilization of wind energy in grid-connected and isolated power systems. In this study, multilayer feed-forward neural network (MLFFNN), support vector regression (SVR), fuzzy inference system (FIS), adaptive neuro-fuzzy inference system (ANFIS), group method of data handling (GMDH) type neural network, ANFIS optimized with particle swarm optimization algorithm (ANFIS-PSO) and ANFIS optimized with genetic algorithm (ANFIS-GA) are developed to predict the time-series wind speed data. The Time-series prediction describes a model that predicts the future values of the system only using the past values. Past data is entered as input and future data to be used for represents MLA output. The developed models are examined on 5-min, 10-min, 15-min and 30-min intervals of wind speed data. The results demonstrated that the GMDH model for all time intervals can successfully predict the time-series wind speed data with a high accuracy. Also, the combination of ANFIS models with PSO and GA algorithms can increase the prediction accuracy of the ANFIS model for all time intervals.

Contents lists available at ScienceDirect

Information Sciences

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## Generalized morphological components based on interval descriptors and *n*-ary aggregation functions

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A B S T R A C T

Morphological perceptrons (MPs) can be characterized as feedforward morphological neural networks (MNNs) with applications in classification and regression. The neuronal aggregation functions of current MP versions are drawn from gray-scale mathematical morphology (MM) that can be described in terms of matrix products in a lattice algebra called minimax algebra. Specifically, MPs have components each of which computes a pair-wise infimum of an erosion and an anti-dilation that can be expressed in terms of products of matrices with entries in a complete l-group extension.

In this paper, we use the novel concept of an interval descriptor and an *n*-ary aggregation function on a bounded poset in order to generalize existing gray-scale and fuzzy morphological components (MCs) of morphological and hybrid morphological/linear perceptrons (HMLPs). In addition, we present several other examples of generalized morphological components (GMCs) that can and will be incorporated as computational units into shallow and deep artificial neural networks.



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## The Kosko Subsethood Fuzzy Associative Memory (KS-FAM): Mathematical Background and Applications in Computer Vision

**Peter Sussner · Estevão L. Esmi · Ivan Villaverde · Manuel Graña**

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**Abstract** Many well-known fuzzy associative memory (FAM) models can be viewed as (fuzzy) morphological neural networks (MNNs) because they perform an operation of (fuzzy) mathematical morphology at every node, possibly followed by the application of an activation function. The vast majority of these FAMs represent distributive models given by single-layer matrix memories. Although the Kosko subsethood FAM (KS-FAM) can also be classified as a fuzzy morphological associative memory (FMAM), the KS-FAM constitutes a two-layer non-distributive model.

In this paper, we prove several theorems concerning the conditions of perfect recall, the absolute storage capacity, and the output patterns produced by the KS-FAM. In addition, we propose a normalization strategy for the training and recall phases of the KS-FAM. We employ this strategy to compare the error correction capabilities of the KS-FAM and other fuzzy and gray-scale associative memories in terms of some experimental results concerning gray-scale image reconstruction. Finally, we apply the KS-FAM to the task of vision-based self-localization in robotics.

**Keywords** Fuzzy associative memory · Morphological neural network · Mathematical morphology · Erosion · Kosko subsethood measure · Gray-scale image · Pattern recognition · Vision-based localization · Mobile robotics

### 1 Introduction

*Fuzzy associative memories* (FAMs) belong to the class of *fuzzy neural networks* (FNNs). An FNN is an *artificial neural network* (ANN) whose input patterns, output patterns, and/or connection weights are fuzzy-valued [14].

We have recently proposed a very general class of FAMs called *fuzzy morphological associative memories* (FMAMs) [59, 62, 63] that includes many well-known models of

# Outras aplicações

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## Some Approaches Based on Interval-Valued Images and $\mathbb{L}$-Fuzzy Mathematical Morphology for Segmenting Images Reconstructed from Noisy Sinograms


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### Abstract

Two-dimensional image reconstruction from projections is a well known research field with different applications and using different sources, e.g., varying from medical imaging to a synchrotron laboratory. In the mathematical sense, we are looking for a two dimensional piecewise function with compact support for which a set of signals - the measurements, so called projections or sinograms - are known *a priori*. After solving the corresponding inverse problem using an appropriate numerical scheme, a collection of reconstructed (gray-scale) images are provided for the final user for further analysis. In practice, the sinogram is often affected by various source of noise which lead to artefacts in the reconstructed images.


### 1 Introduction

With some notable exceptions [3, 27], fuzzy mathematical morphology (FMM) is generally viewed as a successful approach to gray-scale image processing [6]. In fact, operators of fuzzy logic have proven to be valuable tools for various tasks of gray-scale morphological image processing and computer vision including edge detection, image segmentation, and pattern recognition. The main reasons why it was possible to formulate morphological image filters using connectives of fuzzy logic are twofold:

1. Gray-scale images can be modelled as fuzzy sets;
2. Both fuzzy logic and mathematical morphology are deeply rooted in lattice theory.

However, when expressing a gray-scale image as a fuzzy set by simply normalizing its values so as to

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## Linguistic Descriptions for Automatic Generation of Textual Short-Term Weather Forecasts on Real Prediction Data


Alejandro Ramos-Soto, Alberto Jose Bugarín, Senén Barro, and Juan Taboada



*Abstract*—**We present in this paper an application that automatically generates textual short-term weather forecasts for every municipality in Galicia (NW Spain), using the real data provided by the Galician Meteorology Agency (MeteoGalicia). This solution combines in an innovative way computing with perceptions techniques and strategies for linguistic description of data, together with a natural language generation (NLG) system. The application, which is named GALiWeather, extracts relevant information from weather forecast input data and encodes it into intermediate descriptions using linguistic variables and temporal references. These descriptions are later translated into natural language texts by the NLG system. The obtained forecast results have been thoroughly validated by an expert meteorologist from MeteoGalicia using a quality assessment methodology, which covers two key dimensions of a text: the accuracy of its content and the correctness of its form. Following this validation, GALiWeather will be released as a real service, offering custom forecasts for a wide public.**



*Index Terms*—**Computing with perceptions (CWPs), linguistic descriptions of data (LDD), natural language generation (NLG), open data.**


potential consumers. One reason is that the publishing bodies are usually focused on the availability of their datasets rather than on providing tools or means for accessing and processing them. This often results in extensive catalogues of heterogeneous data, which have almost no direct value for the potential consumers of that data.

Besides a lack of standardization, there is also a lack of tools and services which allow a better access and comprehension of the raw data provided by the public institutions. An interesting and illustrative example of these kinds of services can be found in meteorology, where meteorological agencies offer both raw data and also several types of information pieces (such as forecasts, reports, or meteorological warnings) that are elaborated upon by meteorologists from these raw data.

Artificial intelligence provides us with tools that allow us to process and understand this massive availability of huge quantities of data. Originally, this objective has been assumed by the

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## Not So Cute but Fuzzy: Estimating Risk of Sexual Predation in Online Conversations


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*Abstract*—**The sexual exploitation of minors is a known and persistent problem for law enforcement. Assistance in prioritizing cases of sexual exploitation of potentially risky conversations is crucial. While attempts to automatically triage conversations for the risk of sexual exploitation of minors have been attempted in the past, most computational models use features which are not representative of the grooming process that is used by investigators. Accurately annotating an offender corpus for use with machine learning algorithms is difficult because the stages of the grooming process feed into one another and are non-linear. In this paper we propose a method for labeling risk, tied to stages and themes of the grooming process, using fuzzy sets. We develop a neural network model that uses these fuzzy membership functions of each line in a chat as input and predict the risk of interaction.**


### I. Introduction

The sexual exploitation of online youths is a known and persistent problem. The National Center for Missing and Exploited Children (NCMEC) received 10.2 million reports of suspected child exploitation in 2017 [1]. Researchers have suggested the exploitation of minors online is also likely under-reported, due in part to the offender encouraging the minor to keep the interaction a secret and the minor acquiescing to the request [2]. Furthermore, handling the cases we even know about has placed additional strain on

identification of various aspects of the grooming process is difficult because the stages are neither linear nor perfectly discrete [4], [6]. From previous research, we know within the first 20% of a conversation, an offender may engage in several stages of the grooming process including friendship forming, risk assessment, and the sexual stage. We also know the progression through the grooming stages can be gradual both within and between stages[6]. For instance, within the sexual stage offenders will often start with innocuous questions related to a minor's previous romantic relationships but will progress to questions about sexual history, hypotheticals about future encounters, and at times graphic sexual descriptions of fantasy [10], [13]. Furthermore, identification of code span is a known problem within Natural Language Processing literature and is further compounded by the use of chat logs in which subsequent lines may or may not refer to the line prior [14], [15]. As the bounds between stages are not discrete and the code span of a given topic is problematic due to the nature of the conversation structure, fuzzy annotation of grooming-related content is ideal. Through the use of fuzzy annotation, researchers can model the gradual progression and oscillation of various aspects of the grooming process.

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## Um modelo fuzzy para auxiliar na escolha de locais para perfuração de poços artesianos


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**Resumo**. Através de técnicas geofísicas como sondagem elétrica vertical e imageamento elétrico bi e tri-dimensional é possível obter parâmetros do solo como resistividade, espessura e profundidade. Um outro parâmetro obtido é a resistência transversal, que auxilia na identificação de lugares propícios para se

# Publicações na área de fuzzy - Brasil

( TITLE-ABS-KEY ( fuzzy ) AND AFFILCOUNTRY ( brazil ) )

5.495 document results

Select year range to analyze: 1975 to 2022 Analyze

| Year | Documents |
|---|---|
| 2022 | 23 |
| 2021 | 349 |
| 2020 | 379 |
| 2019 | 372 |
| 2018 | 404 |
| 2017 | 280 |
| 2016 | 342 |
| 2015 | 269 |
| 2014 | 293 |

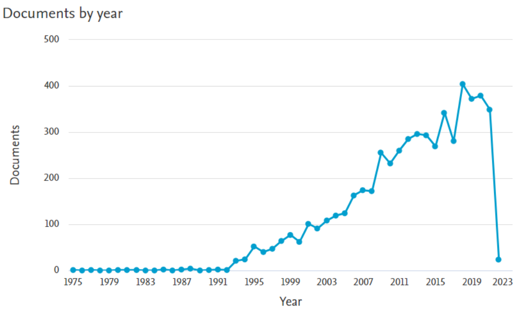


Figura: Número de publicações na área de fuzzy no Brasil, de 1975 a 2022. Fonte: https://www.scopus.com/

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# Obrigado!

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Github: https://viniciuswasques.github.io/home/