Fuzzy vs. Probability

Fuzzy: When we say about certainty of thing

Example: A patient come to the doctor and he has to diagnose so that medicine can be prescribed.

Doctor prescribed a medicine with certainty 60% that the patient is suffering from flue. So, the disease will be cured with certainty of 60% and uncertainty of 40%. Here, instead of flue, other diseases with some other certainties may be.

Probability: When we say about the chance of an event to occur.

Example: India will win this T20 World Cup with a chance 60% means that out of 100 matches, India won 60 matches.

Prediction vs. Forecasting

The Fuzzy vs. Probability is analogical to Prediction vs. Forecasting

Prediction: When you start guessing about the things.

Forecasting: When you take the information from the past job and apply it to new job.

The main differences

Prediction is based on the best guess from experiences.

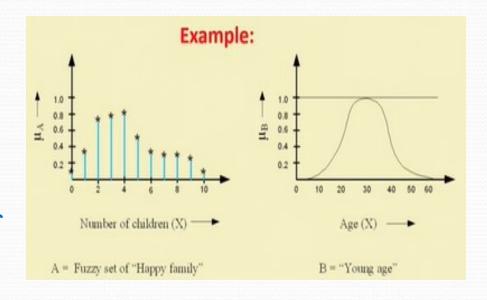
Forecasting is based on data you have actually recorded and packed from previous job.

Fuzzy membership functions

• A fuzzy set is completely characterized by its membership function (sometimes abbreviated as MF and denoted as μ). So, it would be important to learn how a membership function can be expressed (mathematically or otherwise)

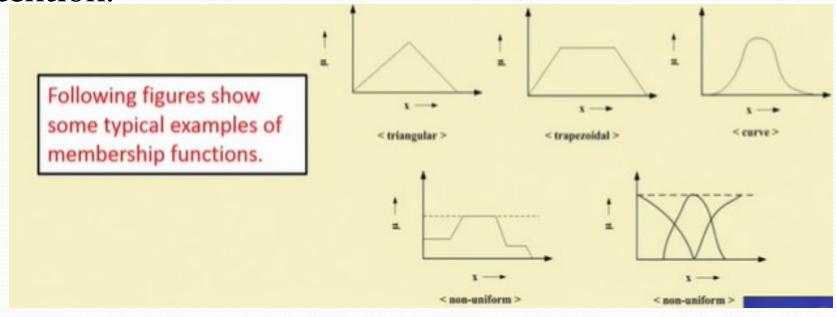
Note: A membership function can be on-

- a) a discrete universe of discourse and
- b) a continuous universe of discourse



Fuzzy membership functions

So membership function on a discrete universe of course is trivial. However a membership function on a continuous universe of discourse needs a special attention.



Fuzzy MFs: Formulation & Parameterization

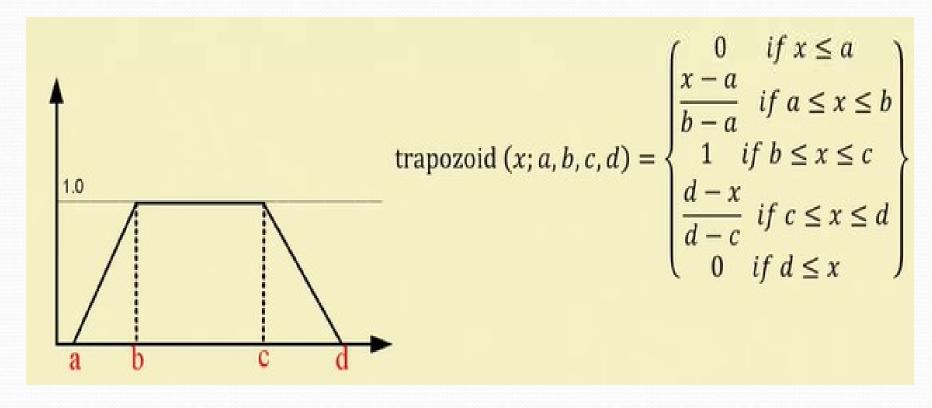
In the following, we try to parameterize the different MFs on a continuous universe of discourse.

Triangular MFs: A triangular MF is specified by three parameter {a, b, c} and can be formulated as follows-

triangle
$$(x; a, b, c) = \begin{cases} 0 & \text{if } x \le a \\ \frac{x - a}{b - a} & \text{if } a \le x \le b \\ \frac{c - x}{c - b} & \text{if } b \le x \le c \end{cases}$$

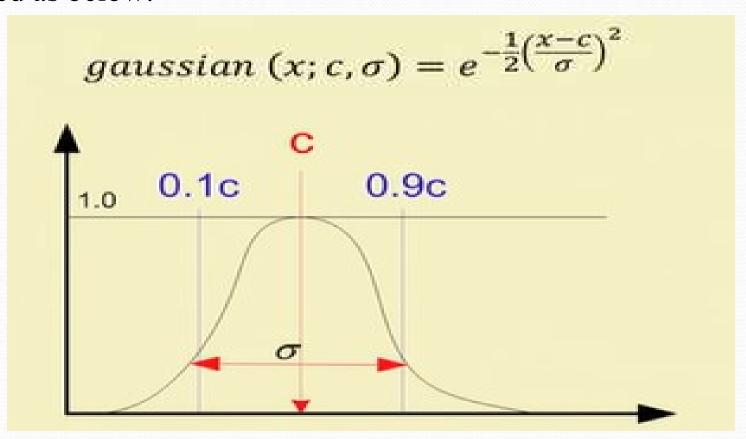
Fuzzy MFs: Trapezoidal

A Trapezoidal MF is specified by four parameters {a, b, c, d} and can be defined as follows:



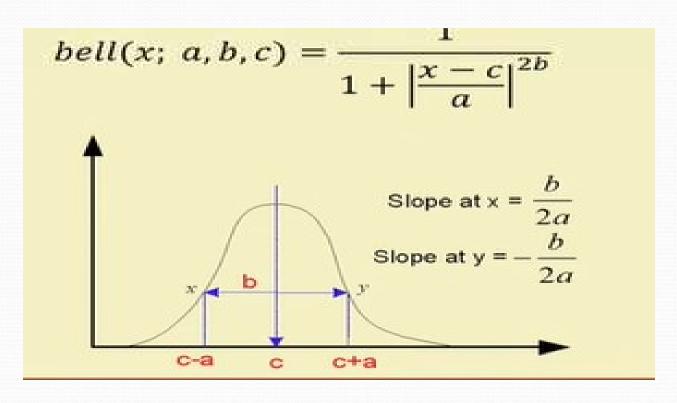
Fuzzy MFs: Gaussian

A Gaussian MF is specified by two parameters $\{c, \sigma\}$ and can be defined as below:



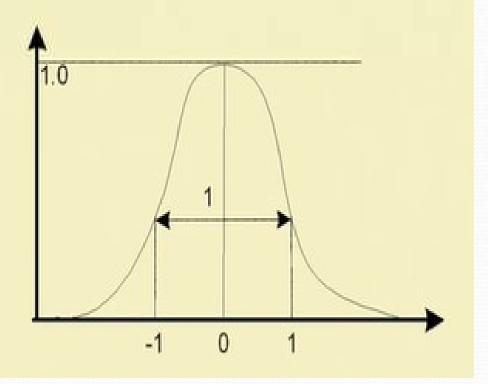
Fuzzy MFs: Generalized Bell

It is also called Cauchy MFs. A Generalized bell MF is specified by three parameters {a, b, c} and is defined as follows-



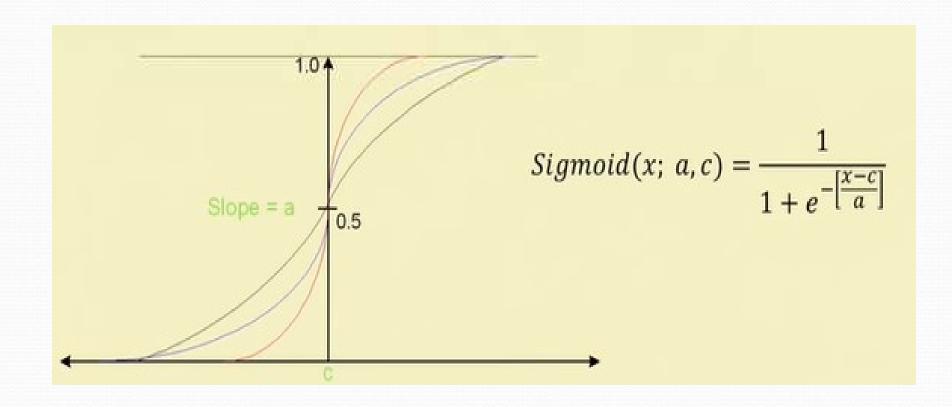
Example: Generalized Bell MF

Example:
$$\mu(x) = \frac{1}{1+|x|^2}$$
;
 $a = b = 1 \text{ and } c = 0$;



Fuzzy MFs: Sigmoidal MFs

Parameters $\{a, c\}$; where c = crossover point and a = slope at c



Fuzzy MFs: Example

Example: Consider the following grading system for a course

Excellent = Marks ≥ 90

Very Good = $75 \le Marks \le 90$

Good = $60 \le Marks \le 70$

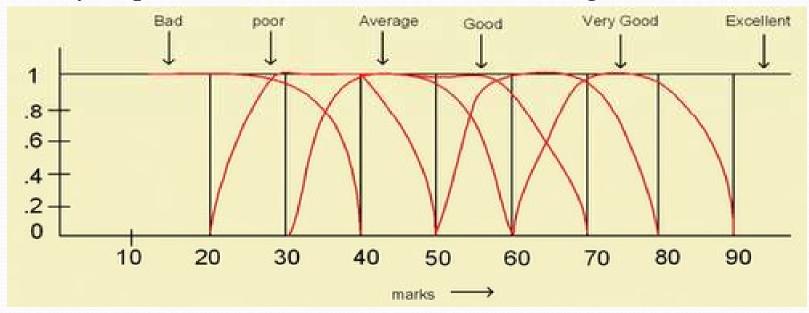
Average = $50 \le Marks \le 60$

Poor = $35 \le Marks \le 50$

Bad = Marks ≤ 35

Grading System

A Fuzzy implementation look like the following



You can decide a standard fuzzy MF for each fuzzy grade

Generation of MFs

Given a membership function of a fuzzy set representing a linguistic hedge, we can derive many more MFs representing several other linguistic hedges using the concept of **Concentration** and **Dilation**.

- 1. Concentration: $A^K = [\mu_A(x)]^K$; K > 1
- **2. Dilation:** $A^{K} = [\mu_{A}(x)]^{K}$; K < 1

Example: Age = { Young, Middle-aged, old}

Thus, corresponding to Young, we have: Not Young, Very Young, Not Very Young and so on.

Similarly, with old, we can have: Not Old, Very Old, Very very Old etc.

Thus, $\mu_{Extremely\ old}(\mathbf{x}) = (((\mu_{old}(\mathbf{x}))^2)^2)^2$

Or, $\mu_{more\ or\ less\ old}(x) = (\mu_{old}(x))^{0.5}$

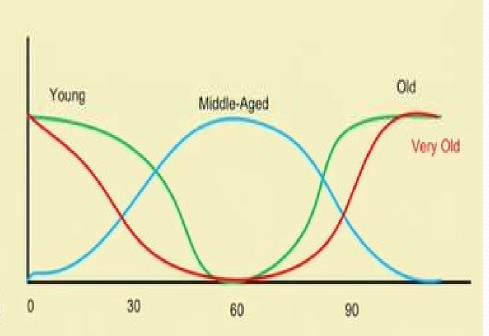
Linguistic variables & values

$$\mu_{young}(x) = \text{bell(x,20,2,0)} = \frac{1}{1 + (\frac{x}{20})^4}$$

$$\mu_{old}(x) = \text{bell(x,30,3,100)} = \frac{1}{1 + (\frac{x - 100}{30})^6}$$

 $\mu_{middle-aged}(x) = bell(x,30,60,50)$

Not young=
$$\overline{\mu_{young}(x)} = 1 - \mu_{young}(x)$$



Young but not too young =
$$\mu_{young}(x) \cap \overline{\mu_{young}(x)}$$

Fuzzy Operations

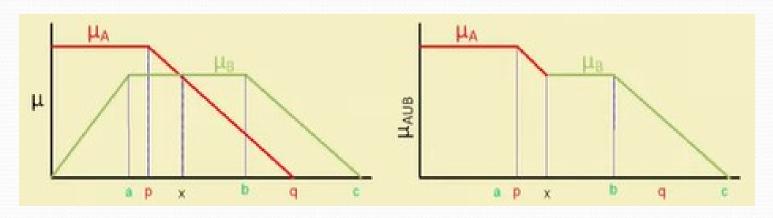
Basic Fuzzy set operation: Union

Union (A U B): $\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x))$

$$A = \{(x_1, 0.5), (x_2, 0.1), (x_3, 0.4)\}$$
 and

B=
$$\{(x_1, 0.2), (x_2, 0.3), (x_3, 0.5)\};$$

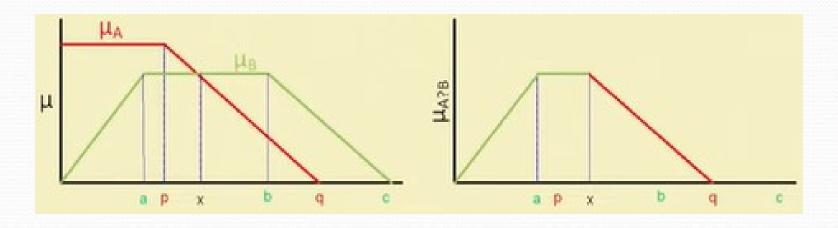
$$C = A \cup B = \{(x_1, 0.5), (x_2, 0.3), (x_3, 0.5)\}$$



Basic Fuzzy set operation: Intersection

Intersection (A \cap B): $\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x))$

A= {
$$(x_1, 0.5), (x_2, 0.1), (x_3, 0.4)$$
} and
B= { $(x_1, 0.2), (x_2, 0.3), (x_3, 0.5)$ };
C=A \cap B = { $(x_1, 0.2), (x_2, 0.1), (x_3, 0.4)$ }

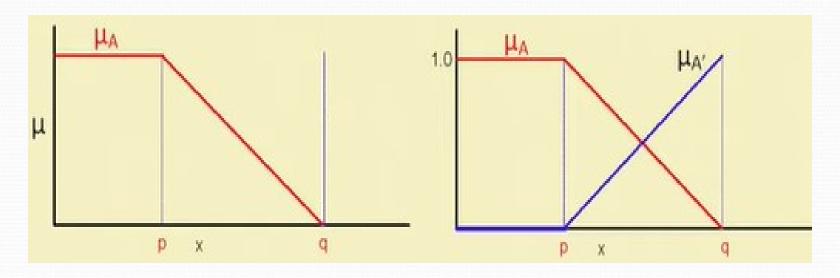


Basic Fuzzy set operation: Complement

Complement (A^C): $\mu_A^C(x) = 1 - \mu_A(x)$

$$A = \{(x_1, 0.5), (x_2, 0.1), (x_3, 0.4)\}$$
 and

$$C = A^{C} = \{(x_1, 0.5), (x_2, 0.9), (x_3, 0.6)\}$$



Basic Fuzzy set operation: Product

Algebric product or Vector product (A · B)

$$\mu_{A \cdot B}(x) = \mu_A(x) \cdot \mu_A(x)$$

Scalar product $(\alpha \times A)$

$$\mu_{\alpha A}(x) = \alpha \times \mu_A(x)$$

Basic Fuzzy set operation: Sum & Difference

Sum (A + B):

$$\mu_{A+B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) \cdot \mu_B(x)$$

Difference (A-B = $A \cap B^C$):

$$\mu_{A-B}(x) = \mu_{A\cap B}^{C}(x)$$

Disjunctive sum:

$$A \bigoplus B = (AC \cap B) \cup (A \cap BC)$$

Bounded sum:

$$|A(x) \oplus B(x)| = \mu_{|A(x) \oplus B(x)|} = \min\{1, \mu_{A}(x) + \mu_{B}(x)\}\$$

Bounded Difference:

$$|A(x) \Theta B(x)| = \mu_{|A(x) \Theta B(x)|} = \max\{0, \mu_{A}(x) + \mu_{B}(x) - 1\}$$

Basic Fuzzy set operation: Equality & Power

Equality (A = B):

$$\mu_{A}(x) = \mu_{B}(x)$$

Power of a Fuzzy set Aa

$$\mu_A{}^{\alpha}(x) = (\mu_A(x))^{\alpha}$$

- ✓ If α < 1, then it is called dilation.
- ✓ If $\alpha > 1$, then it is called concentration.

Basic Fuzzy set operation: Cartesian product

Cartesian product (A × B):

$$\mu_{A \times B} = \min(\mu_A(x), \mu_B(x))$$

$$A(x) = \{(x_1, 0.2), (x_2, 0.3), (x_3, 0.5), (x_4, 0.6)\}$$

$$B(y) = \{(y_1, 0.8), (y_2, 0.6), (y_3, 0.3)\}$$

$$A \times B = \min(\mu_A(x), \mu_B(y)) = \begin{cases} x_1 & y_2 & y_3 \\ x_2 & 0.2 & 0.2 & 0.2 \\ 0.3 & 0.3 & 0.3 \\ x_3 & 0.5 & 0.5 & 0.3 \\ 0.6 & 0.6 & 0.3 \end{cases}$$