

A slide show of our practice note

Fuzzy Data Processing

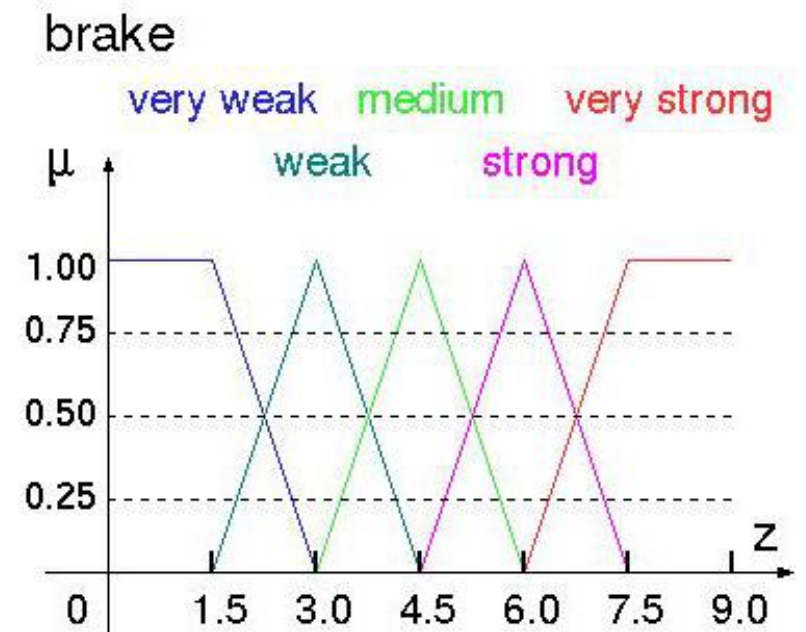
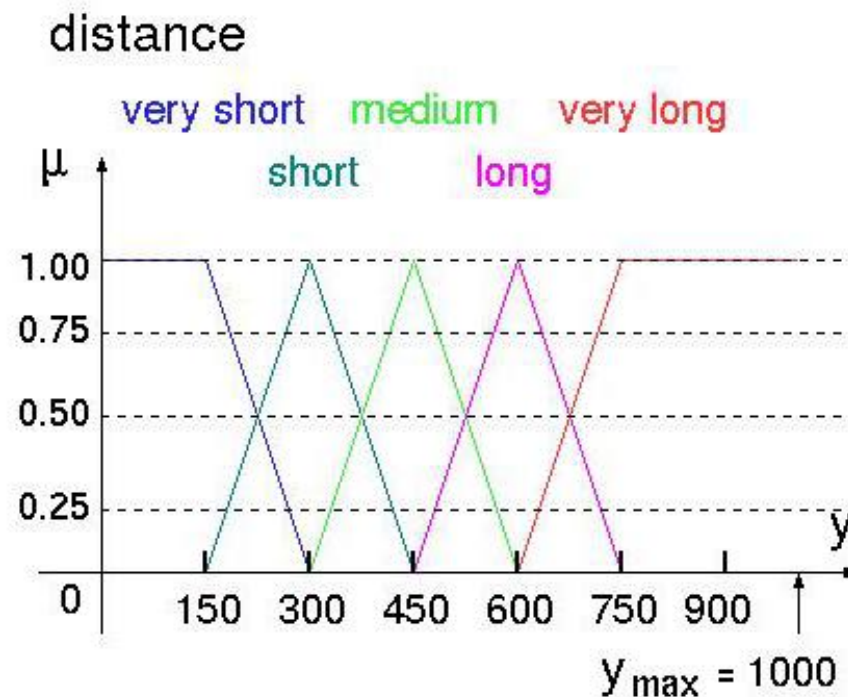
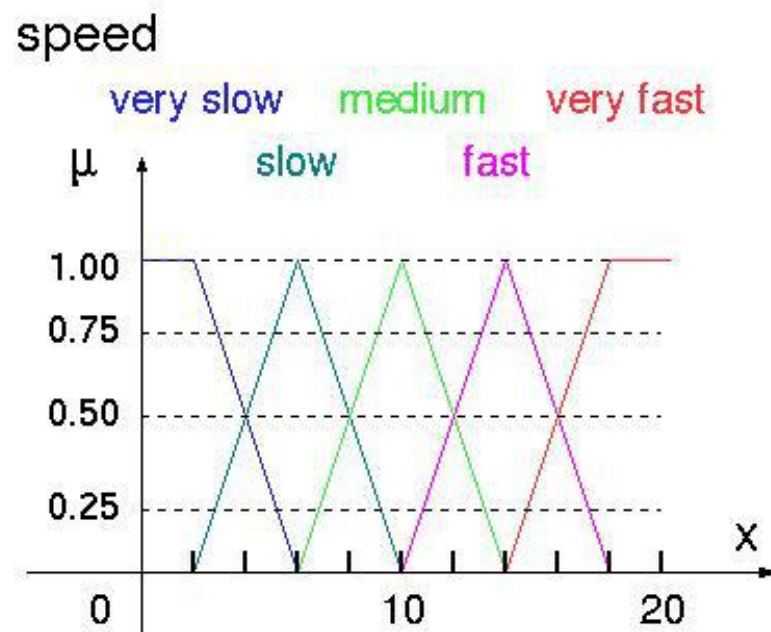
Practice 2020 - online

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Last modified on 18 October 2020

I. How to control two virtual metro cars?

Assume 5 triangle membership functions for each of 3 categories



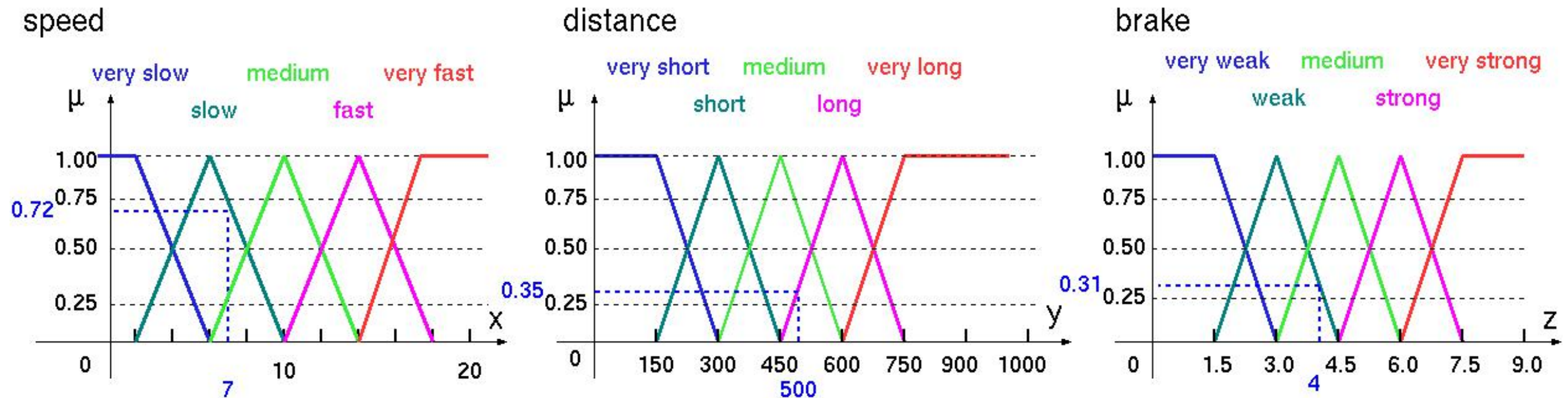
Membership of 3 specific values of speed, distance and brake

Under one rule

IF $x = \text{slow}$ AND $y = \text{long}$ THEN $z = \text{weak}$

Assume now $x = 7$, $y = 500$, $z = 4$

Then the membership value of this rule is $\rightarrow \min\{0.72, 0.35\} \times 0.31 = 1.085$



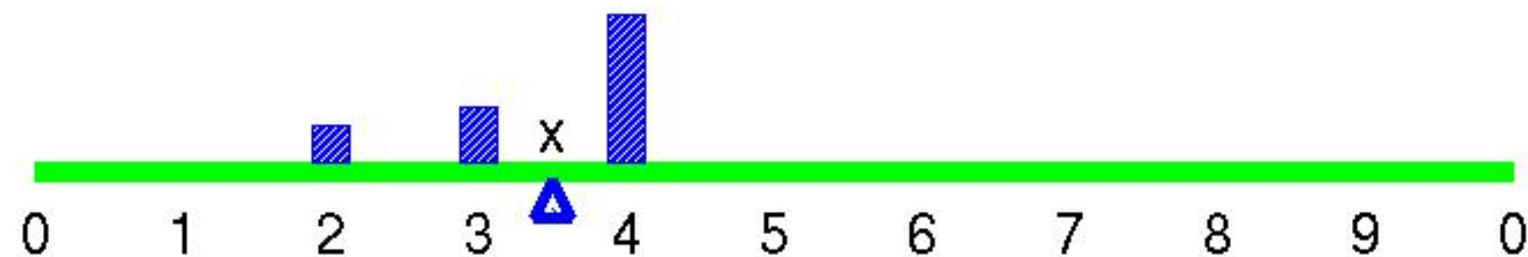
When Speed = 7 and distance = 500

under one rule

IF Speed is slow AND Distance is long THEN Brake is weak

| brake | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|----------------------|--------------|--------------|--------------|--------------|-------|--------------|--------------|--------------|--------------|--------------|--------------|
| The membership value | | | | | 1.085 | | | | | | |
| | \wedge | \wedge | \wedge | \wedge | | \wedge | \wedge | \wedge | \wedge | \wedge | \wedge |
| | 0.000 | 0.000 | 0.175 | 0.350 | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Fuzzify! => The best appropriate value of brake?



$$0.175(x-2) + 0.350(x-3) + 1.085(x-4) = 0 \Rightarrow 1.610x = 5.740 \Rightarrow x = 3.57$$

Membership of 3 specific values of speed, distance and brake

Under two rules

IF $x = \text{slow}$ AND $y = \text{long}$ THEN $z = \text{weak}$

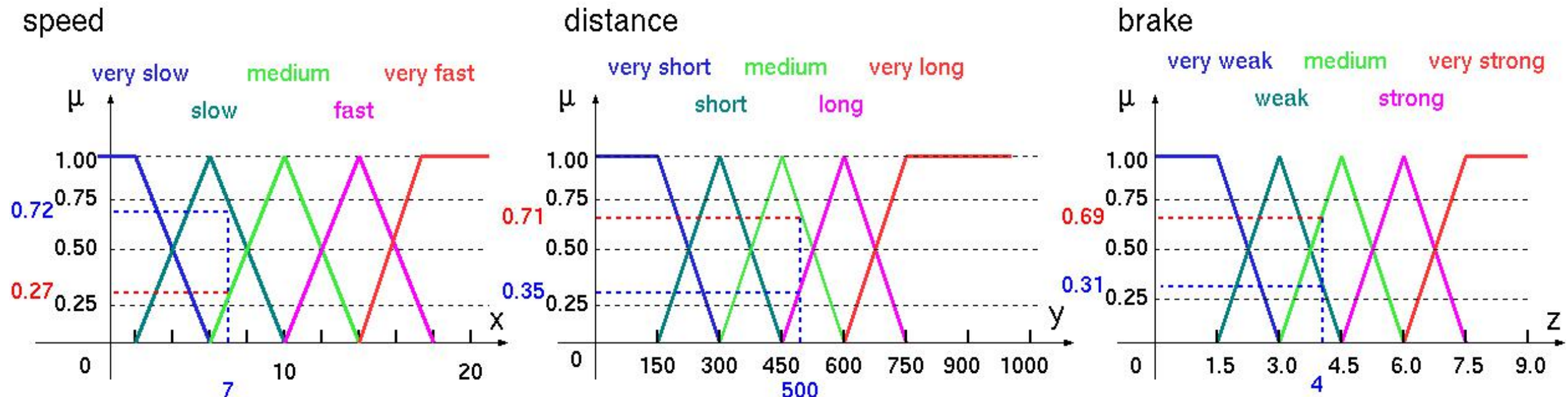
OR

IF $x = \text{medium}$ AND $y = \text{medium}$ THEN $z = \text{medium}$

Assume now $x = 7, y = 500, z = 4$

Then the membership value of these two rules is

$$\max\{\min(0.72, 0.35) \times 0.31, \min(0.27, 0.71) \times 0.69\} = \max\{0.1085, 0.1823\} = 0.1823$$



When Speed = 7 and distance = 500

under two rules

IF Speed is slow AND Distance is long THEN Brake is weak

IF Speed is medium AND Distance is medium THEN Brake is medium

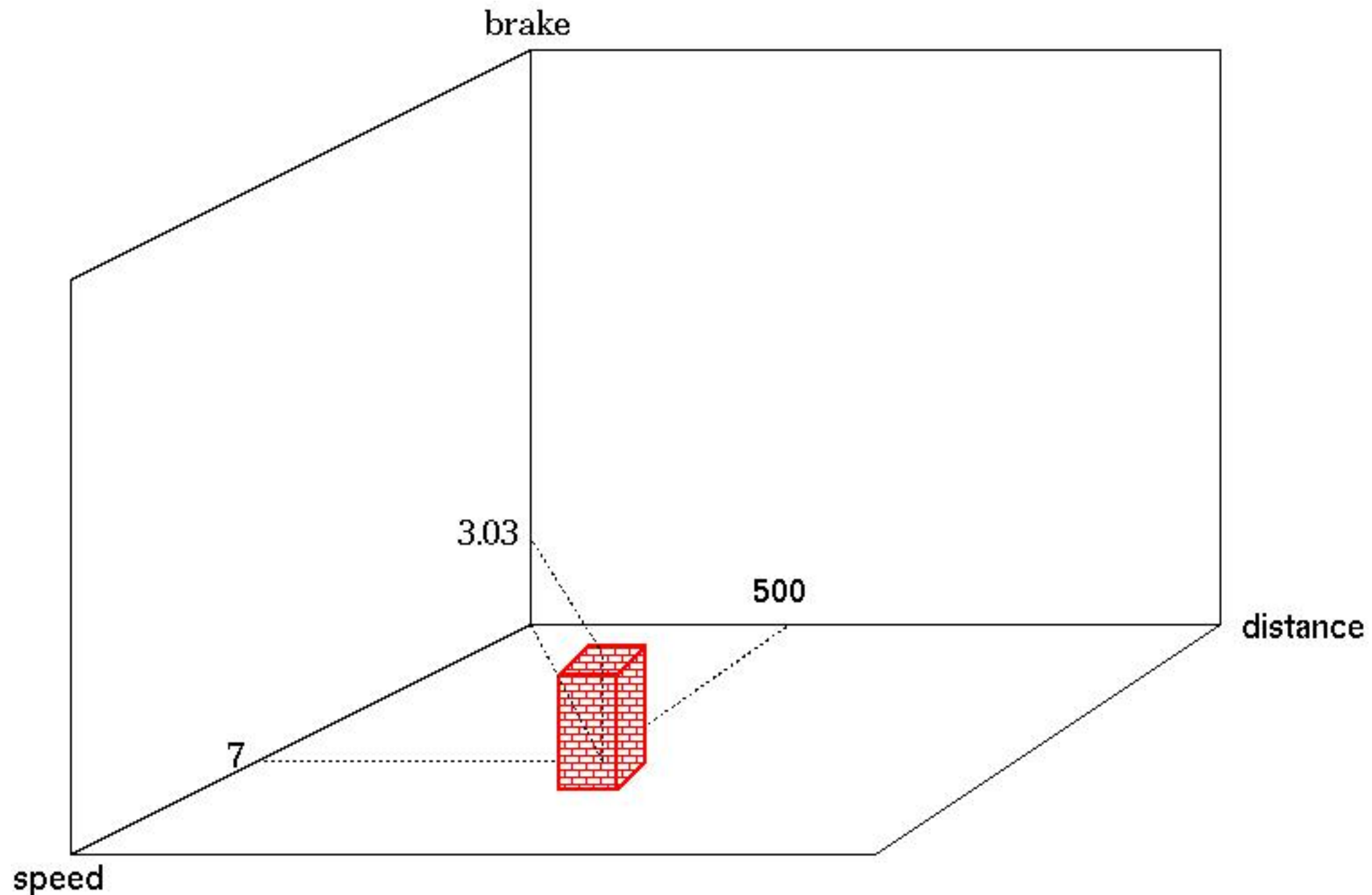
| brake | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|----------------------|--------------|--------------|--------------|--------------|-------|--------------|--------------|--------------|--------------|--------------|--------------|
| The membership value | | | | | 0.182 | | | | | | |
| | \wedge | \wedge | \wedge | \wedge | | \wedge | \wedge | \wedge | \wedge | \wedge | \wedge |
| | 0.000 | 0.000 | 0.175 | 0.350 | | 0.135 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

The best appropriate value of brake?



$$0.175(x-2) + 0.350(x-3) + 0.182(x-4) + 0.135(x-5) = 0 \Rightarrow 0.842x = 2.803 \Rightarrow x = 3.03$$

Let's plot one point of speed-distance-brake in the previous page in 3D space!



What about all other combination of speed and distance?

Practice

Calculate Brake for all possible combinations of speed and distance under 2 rules in the previous page!

[illegible]

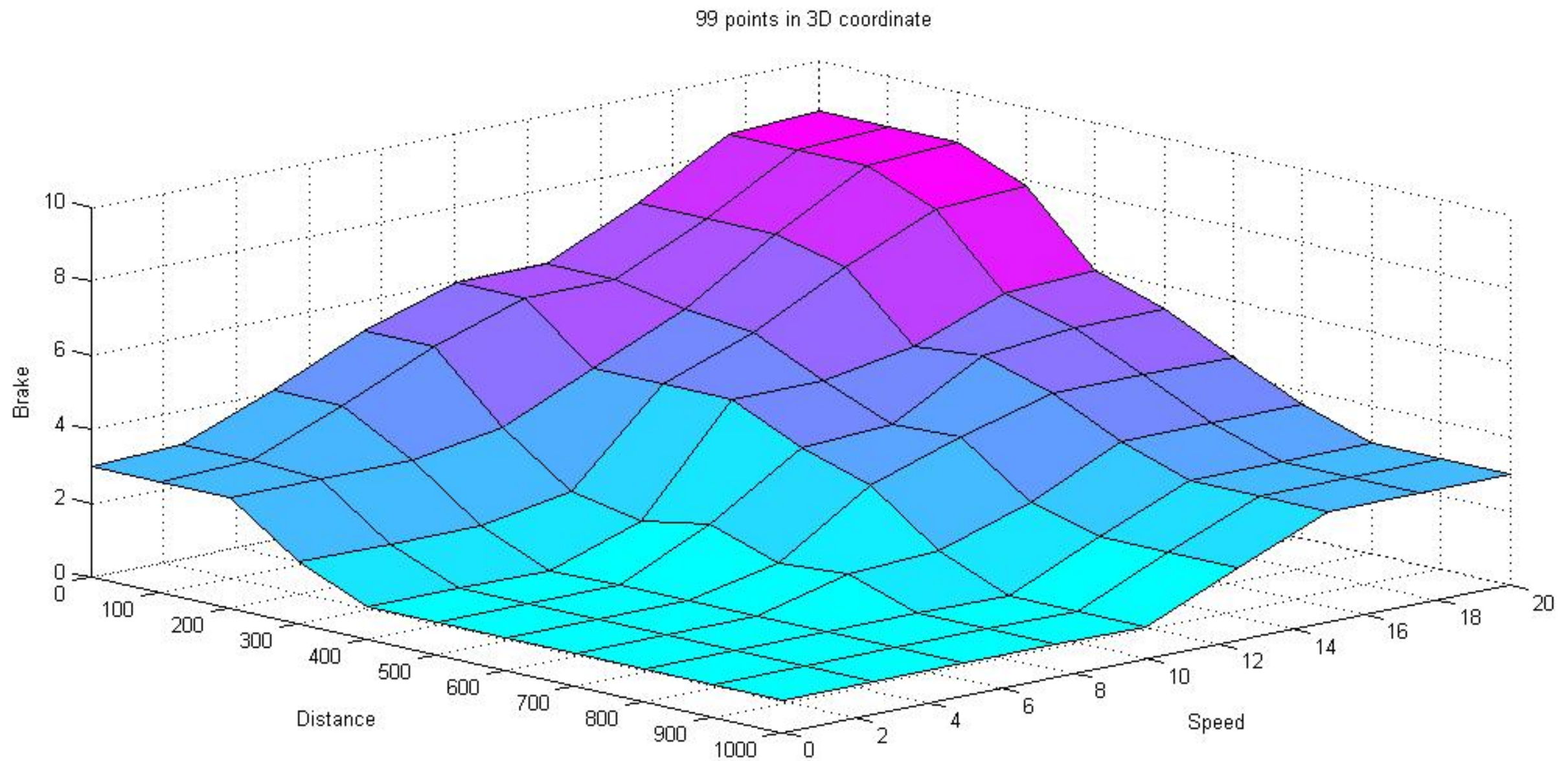
A snapshot of the table under 3 rules

By Bogutskaya Yulia (2016)

| Speed | Distance | Brake | Rule 1: IF x=medium AND y=small THEN z=strong | | | | Rule 2: IF x=medium AND y=medium THEN z=medium | | | | Rule 3: IF x=medium AND y=large THEN z=week | | | | Max of rules | Balance |
|-------|----------|-------|---|------|------|----------------------------|--|------|------|----------------------------|---|------|------|----------------------------|--------------|----------|
| | | | mSp1 | mDs1 | mBr1 | $\min(mSp, mDs) \cdot mBr$ | mSp2 | mDs2 | mBr2 | $\min(mSp, mDs) \cdot mBr$ | mSp3 | mDs3 | mBr3 | $\min(mSp, mDs) \cdot mBr$ | | |
| 11,00 | 500,00 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | 3,727273 |
| | | 1 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | |
| | | 2 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0,25 | 0,125 | 0,125 | |
| | | 3 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 1 | 0,5 | 0,5 | |
| | | 4 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0,75 | 0,375 | 0,75 | 0,5 | 0,25 | 0,125 | 0,375 | |
| | | 5 | 0,75 | 0 | 0,3 | 0 | 0,75 | 0,5 | 0,75 | 0,375 | 0,75 | 0,5 | 0 | 0 | 0,375 | |
| | | 6 | 0,75 | 0 | 1 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | |
| | | 7 | 0,75 | 0 | 0,3 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | |
| | | 8 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | |
| | | 9 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | |
| | | 10 | 0,75 | 0 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0,75 | 0,5 | 0 | 0 | 0 | |
| 11,00 | 550,00 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | 3,285714 |
| | | 1 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | |
| | | 2 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0,25 | 0,1875 | 0,1875 | |
| | | 3 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 1 | 0,75 | 0,75 | |
| | | 4 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0,75 | 0,1875 | 0,75 | 0,75 | 0,25 | 0,1875 | 0,1875 | |
| | | 5 | 0,75 | 0 | 0,3 | 0 | 0,75 | 0,25 | 0,75 | 0,1875 | 0,75 | 0,75 | 0 | 0 | 0,1875 | |
| | | 6 | 0,75 | 0 | 1 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | |
| | | 7 | 0,75 | 0 | 0,3 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | |
| | | 8 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | |
| | | 9 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | |
| | | 10 | 0,75 | 0 | 0 | 0 | 0,75 | 0,25 | 0 | 0 | 0,75 | 0,75 | 0 | 0 | 0 | |
| 11,00 | 600,00 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | 3 |
| | | 1 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | |
| | | 2 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0,25 | 0,1875 | 0,1875 | |
| | | 3 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 1 | 0,75 | 0,75 | |
| | | 4 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0,75 | 0 | 0,75 | 1 | 0,25 | 0,1875 | 0,1875 | |
| | | 5 | 0,75 | 0 | 0,3 | 0 | 0,75 | 0 | 0,75 | 0 | 0,75 | 1 | 0 | 0 | 0 | |
| | | 6 | 0,75 | 0 | 1 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | |
| | | 7 | 0,75 | 0 | 0,3 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | |
| | | 8 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | |
| | | 9 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | |
| | | 10 | 0,75 | 0 | 0 | 0 | 0,75 | 0 | 0 | 0 | 0,75 | 1 | 0 | 0 | 0 | |

3D plot of previous page

By Bogutskaya Yulia (2016)

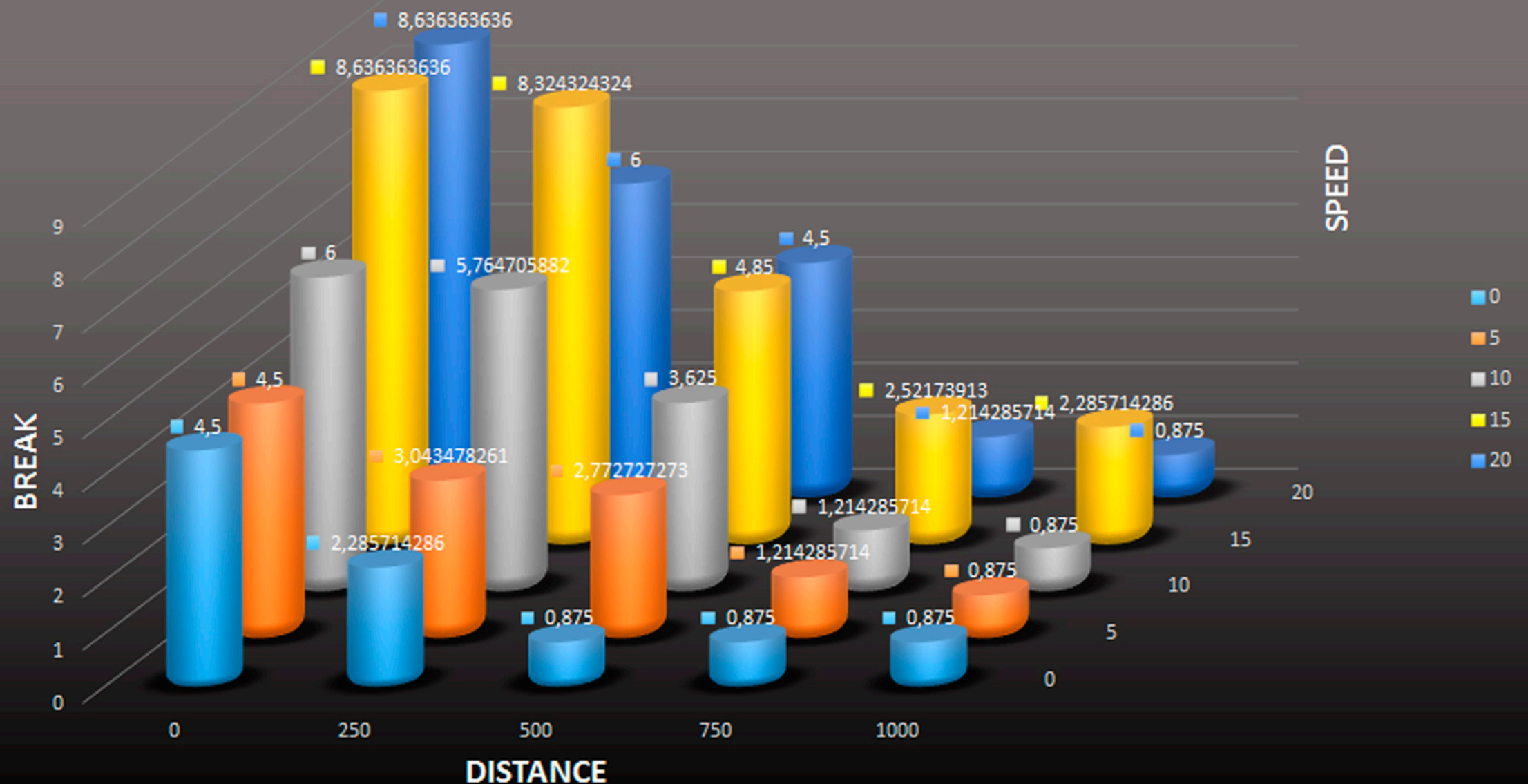


Another example under 24 rules

By Kurilenko Nikita (2016)

| | | | | | | | | | | | | | | | | | | | | | | | | | |
|----------|-----|----------|-------|-------|-------|-----|----------|----------|----------|-------|----|----------|-------|----------|-------|----------|----------|------|----------|----------|----------|-----|-----|----------|-------|
| speed | 0 | 0 | 0 | 0 | 0 | 5 | 5 | 5 | 5 | 5 | 10 | 10 | 10 | 10 | 10 | 15 | 15 | 15 | 15 | 15 | 20 | 20 | 20 | 20 | 20 |
| distance | 0 | 250 | 500 | 750 | 1000 | 0 | 250 | 500 | 750 | 1000 | 0 | 250 | 500 | 750 | 1000 | 0 | 250 | 500 | 750 | 1000 | 0 | 250 | 500 | 750 | 1000 |
| break | 4,5 | 2,285714 | 0,875 | 0,875 | 0,875 | 4,5 | 3,043478 | 2,772727 | 1,214286 | 0,875 | 6 | 5,764706 | 3,625 | 1,214286 | 0,875 | 8,636364 | 8,324324 | 4,85 | 2,521739 | 2,285714 | 8,636364 | 6 | 4,5 | 1,214286 | 0,875 |

| | | | | | | | | | | | | | | | | | | | | | | | | | |
|-----------------|--------|--------|--------|-------|-------|--------|--------|--------|------|-------|--------|--------|--------|--------|--------|---------|---------|--------|--------|-------|---------|---------|--------|--------|-------|
| IF speed IS | vSLOW | vSLOW | vSLOW | vSLOW | vSLOW | SLOW | SLOW | SLOW | SLOW | SLOW | MEDIUM | MEDIUM | MEDIUM | MEDIUM | MEDIUM | FAST | FAST | FAST | FAST | FAST | vFAST | vFAST | vFAST | vFAST | vFAST |
| AND distance IS | vSHORT | SHORT | MEDIUM | LONG | vLONG | vSHORT | SHORT | MEDIUM | LONG | vLONG | vSHORT | SHORT | MEDIUM | LONG | vLONG | vSHORT | SHORT | MEDIUM | LONG | vLONG | vSHORT | SHORT | MEDIUM | LONG | vLONG |
| THEN break IS | MEDIUM | MEDIUM | WEAK | WEAK | WEAK | MEDIUM | MEDIUM | MEDIUM | WEAK | vWEAK | STRONG | STRONG | MEDIUM | WEAK | vWEAK | vSTRONG | vSTRONG | STRONG | MEDIUM | WEAK | vSTRONG | vSTRONG | STRONG | MEDIUM | WEAK |



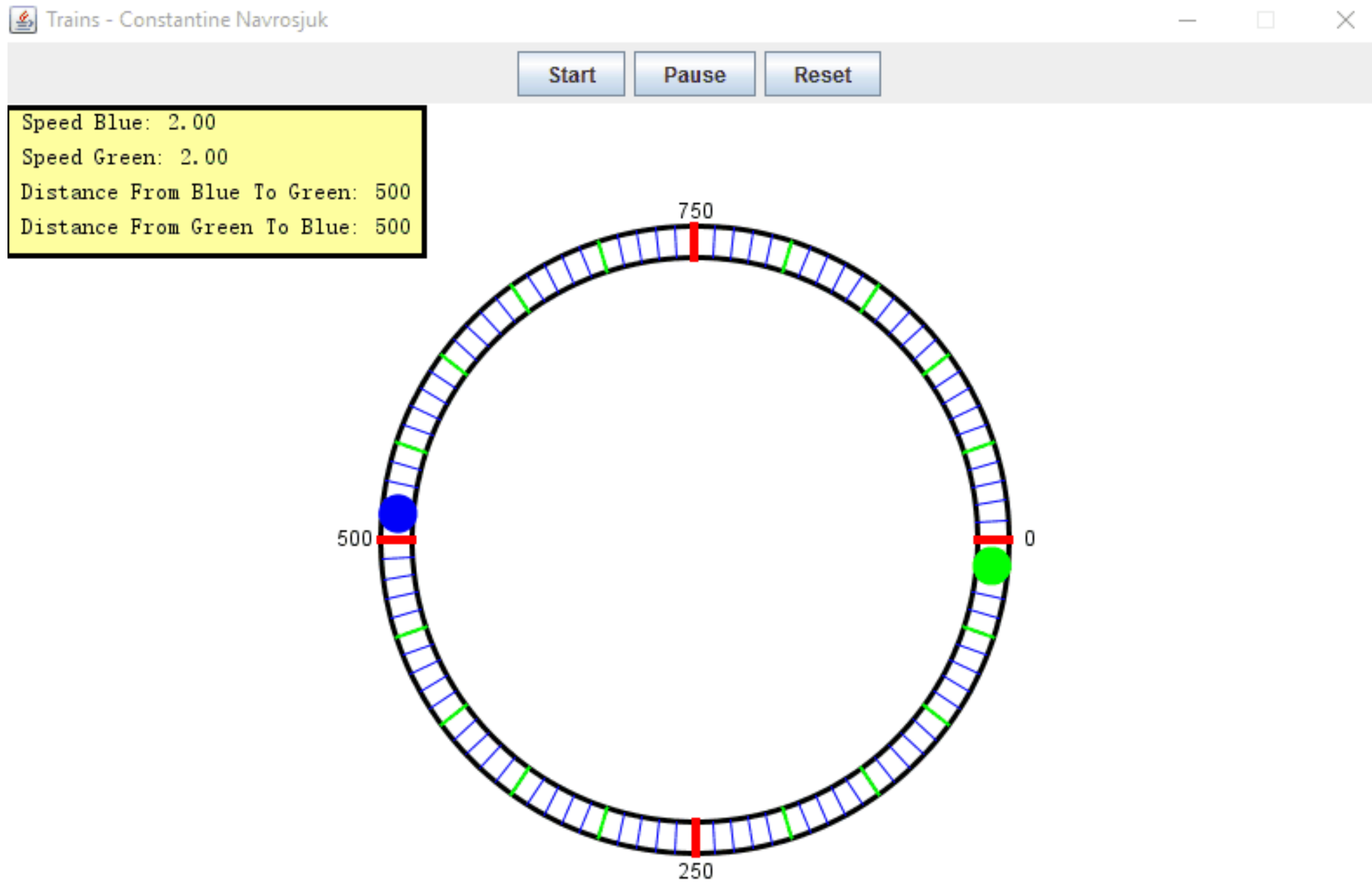
practice

X: speed Y: distance Z_i : defuzzified brake Z: brake

[illegible]

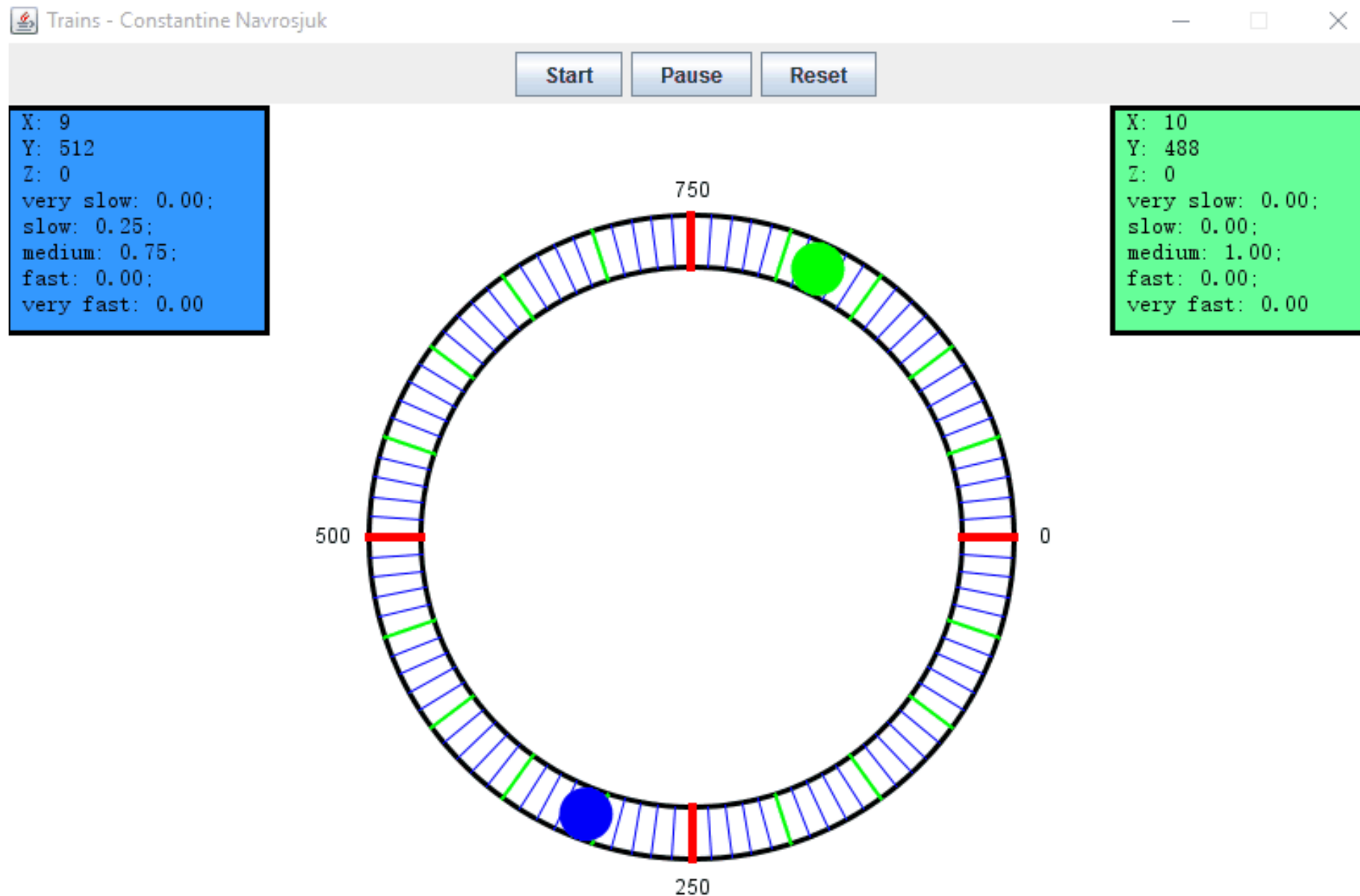
Two metro cars in one loop with constant speed - animation

By Navrosjuk Kostia (2016)



Two metros in one loop when speed changes at random

By Navrosjuk Kostia (2016)



**Then avoid crash of two metro cars
by using appropriate value of your own
10 rules in each step!**

II. Classify Iris Flowers!

Iris Flower Database to design



| Setosa | | | | Versicolor | | | | Virginica | | | |
|--------|-------|-------|-------|------------|-------|-------|-------|-----------|-------|-------|-------|
| x_1 | x_2 | x_3 | x_4 | x_1 | x_2 | x_3 | x_4 | x_1 | x_2 | x_3 | x_4 |
| 0.56 | 0.66 | 0.20 | 0.08 | 0.84 | 0.66 | 0.67 | 0.52 | 0.85 | 0.57 | 0.84 | 0.72 |
| 0.62 | 0.70 | 0.22 | 0.04 | 0.66 | 0.61 | 0.57 | 0.56 | 0.91 | 0.82 | 0.88 | 1.00 |
| 0.68 | 0.84 | 0.22 | 0.08 | 0.63 | 0.45 | 0.51 | 0.40 | 0.82 | 0.73 | 0.74 | 0.80 |
| 0.61 | 0.77 | 0.23 | 0.08 | 0.75 | 0.68 | 0.61 | 0.60 | 0.81 | 0.61 | 0.77 | 0.76 |
| 0.61 | 0.68 | 0.20 | 0.04 | 0.76 | 0.50 | 0.58 | 0.40 | 0.86 | 0.68 | 0.80 | 0.84 |
| 0.54 | 0.68 | 0.16 | 0.04 | 0.77 | 0.66 | 0.68 | 0.56 | 0.72 | 0.57 | 0.72 | 0.80 |
| 0.73 | 0.91 | 0.17 | 0.08 | 0.71 | 0.66 | 0.52 | 0.52 | 0.73 | 0.64 | 0.74 | 0.96 |
| 0.72 | 1.00 | 0.22 | 0.16 | 0.85 | 0.70 | 0.64 | 0.56 | 0.81 | 0.73 | 0.77 | 0.92 |
| 0.68 | 0.89 | 0.19 | 0.16 | 0.71 | 0.68 | 0.65 | 0.60 | 0.82 | 0.68 | 0.80 | 0.72 |
| 0.65 | 0.80 | 0.20 | 0.12 | 0.73 | 0.61 | 0.59 | 0.40 | 0.97 | 0.86 | 0.97 | 0.88 |
| 0.72 | 0.86 | 0.25 | 0.12 | 0.78 | 0.50 | 0.65 | 0.60 | 0.97 | 0.59 | 1.00 | 0.92 |
| 0.65 | 0.86 | 0.22 | 0.12 | 0.71 | 0.57 | 0.57 | 0.44 | 0.76 | 0.50 | 0.72 | 0.60 |
| 0.68 | 0.77 | 0.25 | 0.08 | 0.75 | 0.73 | 0.70 | 0.72 | 0.87 | 0.73 | 0.83 | 0.92 |
| 0.65 | 0.84 | 0.22 | 0.16 | 0.77 | 0.64 | 0.58 | 0.52 | 0.71 | 0.64 | 0.71 | 0.80 |
| 0.58 | 0.82 | 0.14 | 0.08 | 0.80 | 0.57 | 0.71 | 0.60 | 0.97 | 0.64 | 0.97 | 0.80 |
| 0.65 | 0.75 | 0.25 | 0.20 | 0.77 | 0.64 | 0.68 | 0.48 | 0.80 | 0.61 | 0.71 | 0.72 |
| 0.61 | 0.77 | 0.28 | 0.08 | 0.81 | 0.66 | 0.62 | 0.52 | 0.85 | 0.75 | 0.83 | 0.84 |

The original **x1** values of 3 families of iris flower
and
determination the range of Large, Medium and Small.

Original data of x_1

Setosa Versicolor Virginica

| | | |
|------|------|------|
| 0.56 | 0.84 | 0.85 |
| 0.62 | 0.66 | 0.91 |
| 0.68 | 0.63 | 0.82 |
| 0.61 | 0.75 | 0.81 |
| 0.61 | 0.76 | 0.86 |
| 0.54 | 0.77 | 0.72 |
| 0.73 | 0.71 | 0.73 |
| 0.72 | 0.85 | 0.81 |
| 0.68 | 0.71 | 0.82 |
| 0.65 | 0.73 | 0.97 |
| 0.72 | 0.78 | 0.97 |
| 0.65 | 0.71 | 0.76 |
| 0.68 | 0.75 | 0.87 |
| 0.65 | 0.77 | 0.71 |
| 0.58 | 0.80 | 0.97 |
| 0.65 | 0.77 | 0.80 |
| 0.61 | 0.81 | 0.85 |

 \Rightarrow

Sort

all data in 3 columns
with descending order
and then
divided into 3 category

0.97 ... 0.80 0.78 ... 0.71 0.68 ... 0.64

Large

Medium

short

Large Medium short

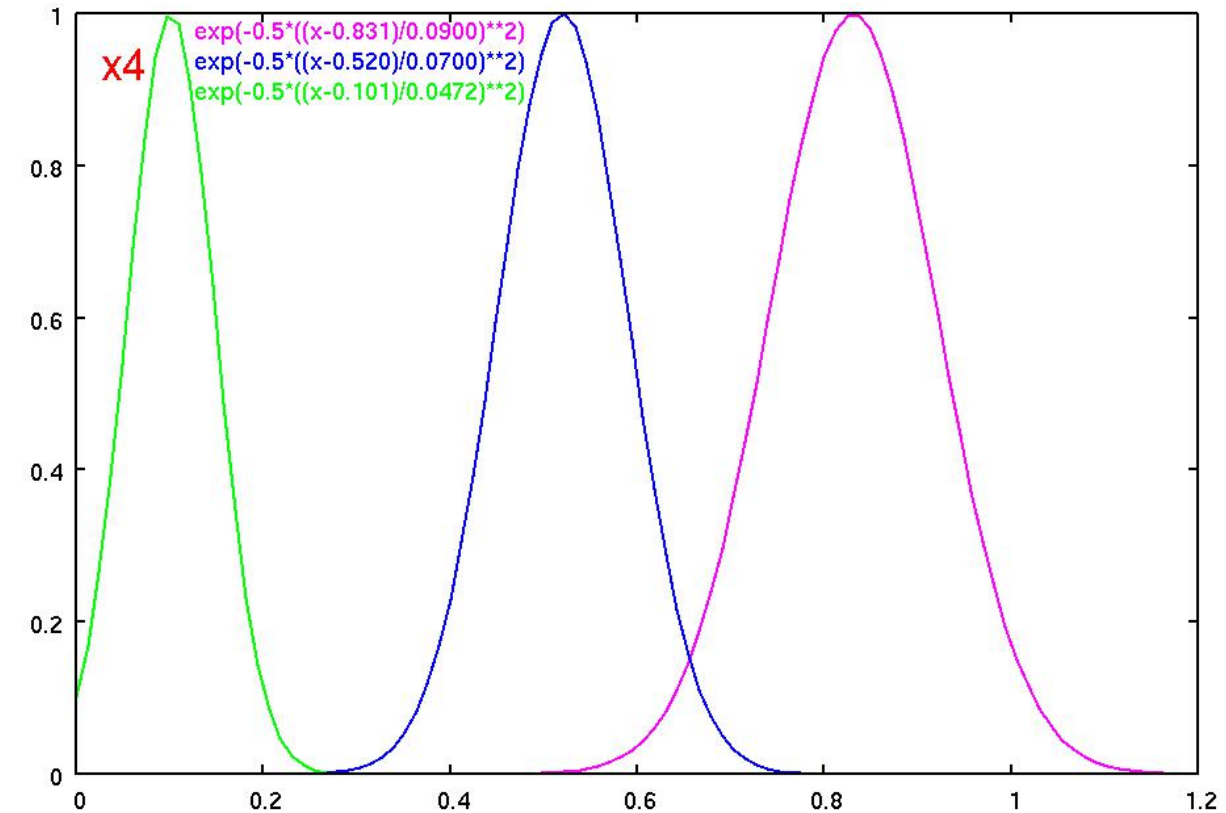
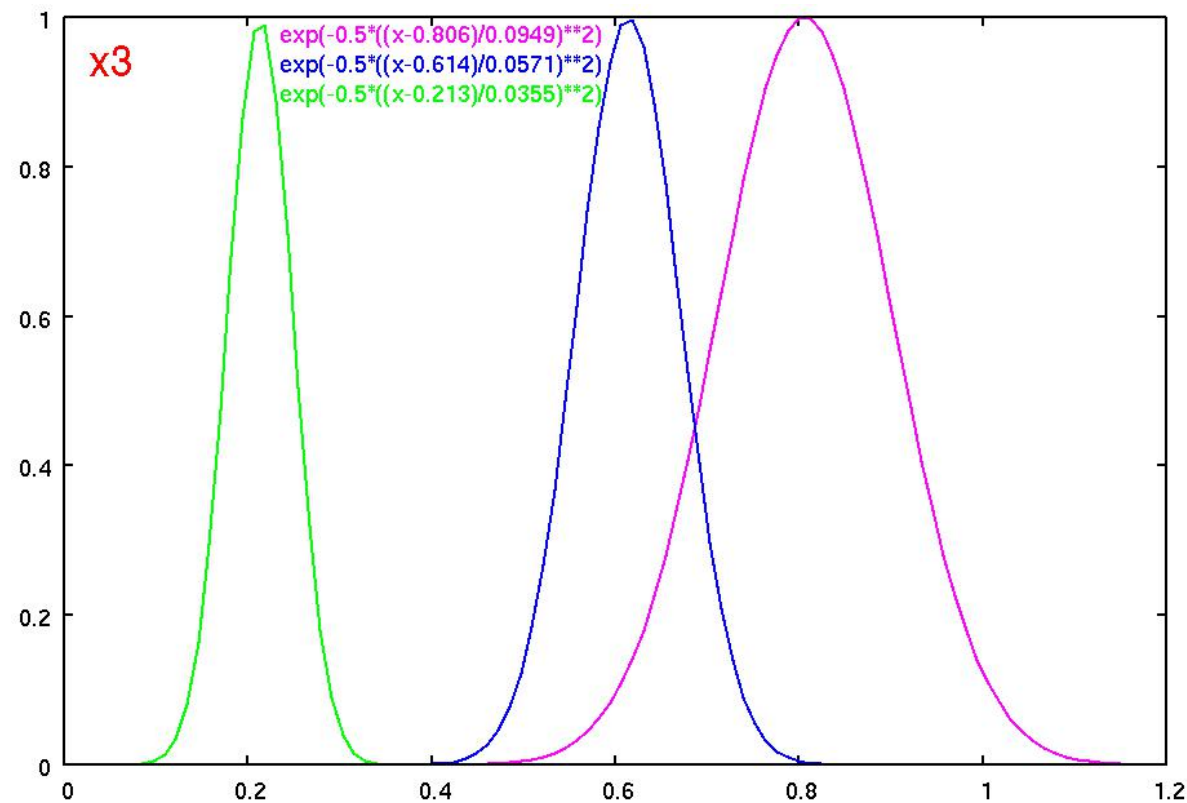
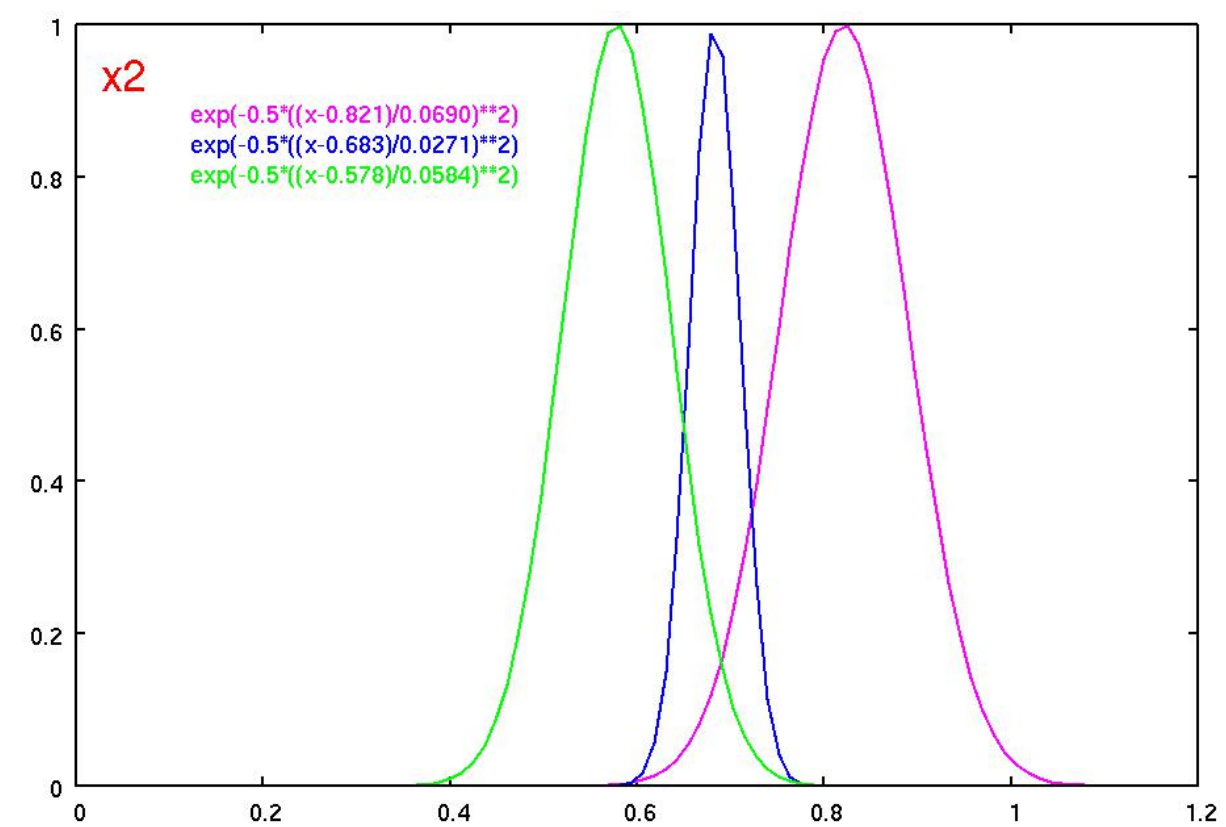
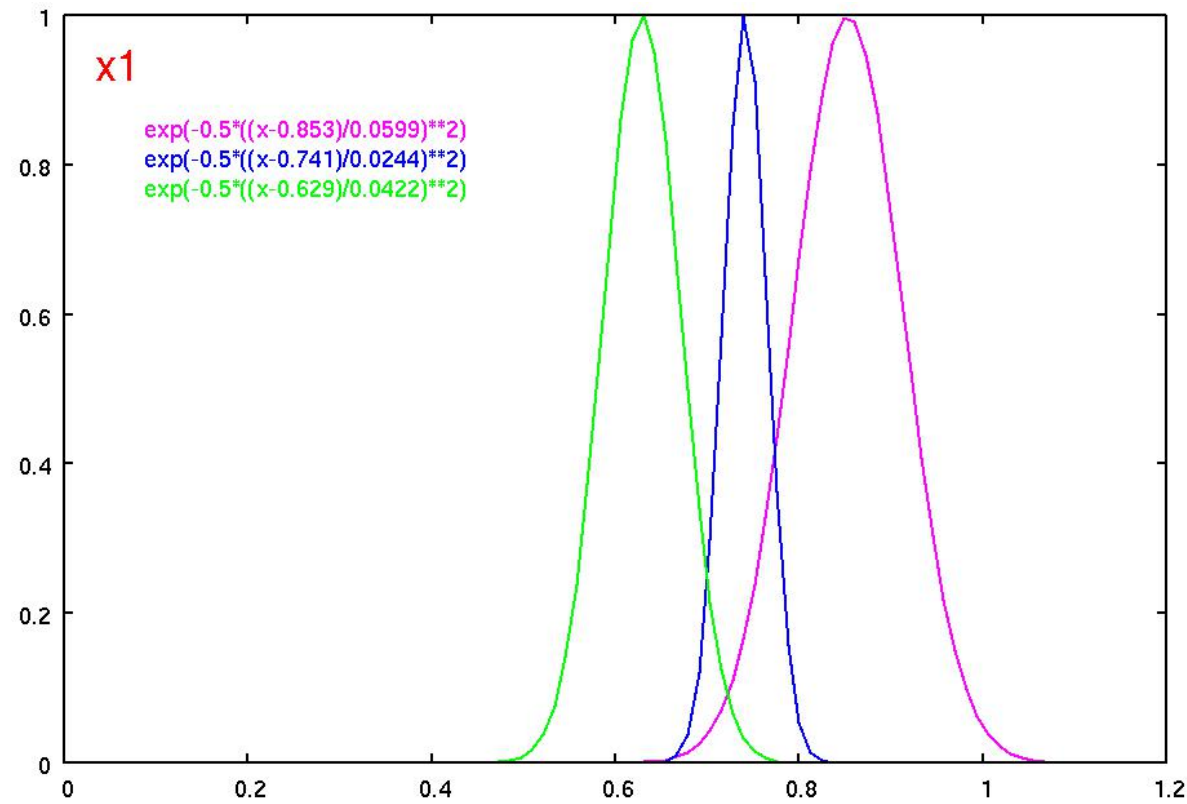
| | | |
|------|------|------|
| 0.97 | 0.78 | 0.68 |
| 0.97 | 0.77 | 0.68 |
| 0.97 | 0.77 | 0.68 |
| 0.91 | 0.77 | 0.66 |
| 0.87 | 0.76 | 0.65 |
| 0.86 | 0.76 | 0.65 |
| 0.85 | 0.75 | 0.65 |
| 0.85 | 0.75 | 0.66 |
| 0.85 | 0.73 | 0.63 |
| 0.84 | 0.73 | 0.62 |
| 0.82 | 0.73 | 0.61 |
| 0.82 | 0.72 | 0.61 |
| 0.81 | 0.72 | 0.61 |
| 0.81 | 0.72 | 0.58 |
| 0.81 | 0.71 | 0.56 |
| 0.80 | 0.71 | 0.64 |
| 0.80 | 0.71 | |

| | | | |
|-----|--------|--------|--------|
| avg | 0.853 | 0.741 | 0.629 |
| std | 0.0599 | 0.0244 | 0.0422 |

In this way we get:

| | | Large | Medium | short |
|----|-----|---------------|---------------|---------------|
| x1 | | 0.97 ... 0.80 | 0.78 ... 0.71 | 0.68 ... 0.64 |
| | avg | 0.853 | 0.741 | 0.629 |
| | std | 0.0599 | 0.0244 | 0.0422 |
| x2 | | 1.00 ... 0.75 | 0.73 ... 0.66 | 0.64 ... 0.45 |
| | avg | 0.821 | 0.683 | 0.578 |
| | std | 0.0690 | 0.0271 | 0.0584 |
| x3 | | 1.00 ... 0.71 | 0.70 ... 0.51 | 0.28 ... 0.14 |
| | avg | 0.806 | 0.613 | 0.213 |
| | std | 0.0949 | 0.0571 | 0.0355 |
| x4 | | 1.00 ... 0.72 | 0.60 ... 0.40 | 0.20 ... 0.04 |
| | avg | 0.831 | 0.520 | 0.101 |
| | std | 0.0900 | 0.0700 | 0.0472 |

Membership function of Small, Medium and Large for x1, x2, x3, and x4



Now let's translate numerical values into human language

Setosa

| x1 | x2 | x3 | x4 |
|--------|--------|-------|-------|
| small | medium | small | small |
| small | medium | small | small |
| small | large | small | small |
| small | large | small | small |
| small | medium | small | small |
| small | medium | small | small |
| medium | large | small | small |
| medium | large | small | small |
| small | large | small | small |
| small | large | small | small |
| medium | large | small | small |
| small | large | small | small |
| small | large | small | small |
| small | large | small | small |
| small | large | small | small |
| small | large | small | small |

Versicolor

| x1 | x2 | x3 | x4 |
|--------|--------|--------|--------|
| large | medium | medium | medium |
| small | medium | medium | medium |
| small | large | medium | medium |
| medium | large | medium | medium |
| medium | medium | medium | medium |
| medium | medium | medium | medium |
| large | large | medium | medium |
| medium | large | medium | medium |
| small | large | medium | medium |
| small | large | medium | medium |
| medium | large | medium | medium |
| medium | large | medium | medium |
| medium | large | medium | large |
| medium | large | medium | medium |
| large | large | large | medium |
| medium | large | medium | medium |
| large | large | medium | medium |

Virginica

| x1 | x2 | x3 | x4 |
|--------|--------|-------|--------|
| large | small | large | large |
| large | large | large | large |
| large | medium | large | large |
| large | small | large | large |
| large | medium | large | large |
| large | small | large | large |
| medium | small | large | large |
| medium | medium | large | large |
| large | medium | large | large |
| large | large | large | large |
| large | small | large | large |
| large | medium | large | large |
| medium | medium | large | medium |
| large | medium | large | large |
| medium | small | large | large |
| large | small | large | large |
| large | large | large | large |

Rules to classify iris flowers

E.g.

R_1 : IF $x_1 =$ small AND $x_2 =$ large AND $x_3 =$ small AND $x_4 =$ small THEN $y = 1$

OR

R_2 : IF $x_1 =$ medium AND $x_2 =$ large AND $x_3 =$ medium AND $x_4 =$ medium THEN $y = 2$

OR

R_3 : IF $x_1 =$ large AND $x_2 =$ small AND $x_3 =$ large AND $x_4 =$ large THEN $y = 3$

OR

R_4 : IF $x_1 =$ large AND $x_2 =$ medium AND $x_3 =$ large AND $x_4 =$ large THEN $y = 3$

which family the next irises belongs to?

$x_1 = 0.80, x_2 = 0.75, x_3 = 0.87$ and $x_4 = 1.00$

| | x1 | x2 | x3 | x4 | y |
|-----|--------|--------|--------|--------|---|
| R1: | small | large | small | small | 1 |
| R2: | medium | large | medium | medium | 2 |
| R3: | large | small | large | large | 3 |
| R4: | large | medium | large | large | 3 |

$$y = \{ \sum_{k=1}^H (M_k(x) \cdot g_k) / \{ \sum_{k=1}^H (M_k(x)) \} \quad (H = 4 \text{ and } j = 1, 2, 3, 4)$$

where

$$M_k(x) = \prod_{i=1}^M \mu_{ik}(x_i) \quad (M = 4)$$

k = index of rule, H = number of rule, M = number of attribute

| | X1 | X2 | X3 | X5 |
|---------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| Large: | $\exp(-0.5((x-0.853)/0.0599)^2)$ | $\exp(-0.5((x-0.821)/0.0690)^2)$ | $\exp(-0.5((x-0.806)/0.0949)^2)$ | $\exp(-0.5((x-0.831)/0.0900)^2)$ |
| Medium: | $\exp(-0.5((x-0.741)/0.0244)^2)$ | $\exp(-0.5((x-0.683)/0.0271)^2)$ | $\exp(-0.5((x-0.614)/0.0571)^2)$ | $\exp(-0.5((x-0.520)/0.0700)^2)$ |
| Small: | $\exp(-0.5((x-0.629)/0.0422)^2)$ | $\exp(-0.5((x-0.578)/0.0584)^2)$ | $\exp(-0.5((x-0.213)/0.0355)^2)$ | $\exp(-0.5((x-0.101)/0.0472)^2)$ |

$\mu_{11} = \exp(-0.5((0.80-0.629)/0.0422)^2) = 0.000$: $\mu_{12} = \exp(-0.5((0.75-0.821)/0.0690)^2) = 0.589$: $\mu_{13} = \exp(-0.5((0.87-0.213)/0.0355)^2) = 0.000$: $\mu_{14} = \exp(-0.5((1.00-0.101)/0.0472)^2) = 0.000$
 $\mu_{21} = \exp(-0.5((0.80-0.741)/0.0244)^2) = 0.054$: $\mu_{22} = \exp(-0.5((0.75-0.821)/0.0690)^2) = 0.589$: $\mu_{23} = \exp(-0.5((0.87-0.614)/0.0571)^2) = 0.000$: $\mu_{24} = \exp(-0.5((1.00-0.520)/0.0700)^2) = 0.000$
 $\mu_{31} = \exp(-0.5((0.80-0.853)/0.0599)^2) = 0.068$: $\mu_{32} = \exp(-0.5((0.75-0.578)/0.0584)^2) = 0.013$: $\mu_{33} = \exp(-0.5((0.87-0.806)/0.0949)^2) = 0.797$: $\mu_{34} = \exp(-0.5((1.00-0.831)/0.0900)^2) = 0.172$
 $\mu_{41} = \exp(-0.5((0.80-0.853)/0.0599)^2) = 0.068$: $\mu_{42} = \exp(-0.5((0.75-0.683)/0.0271)^2) = 0.047$: $\mu_{43} = \exp(-0.5((0.87-0.806)/0.0949)^2) = 0.797$: $\mu_{44} = \exp(-0.5((1.00-0.831)/0.0900)^2) = 0.172$

$$M1 = 0.000 \times 0.589 \times 0.000 \times 0.000 = 0.00000000$$

$$M2 = 0.054 \times 0.589 \times 0.000 \times 0.000 = 0.00000000$$

$$M3 = 0.068 \times 0.013 \times 0.797 \times 0.172 = 0.00012118$$

$$M4 = 0.068 \times 0.047 \times 0.797 \times 0.171 = 0.00043812$$

$$y = (0.00000000 \times 1 + 0.00000000 \times 2 + 0.00012118 \times 3 + 0.00043812 \times 3) / (0.00000000 + 0.00000000 + 0.00012118 + 0.00043812) = 0.00167790 / 0.0005593 = 3.0$$

Banana dataset

(extracted from UCI (University of California, Irvine) Machine Learning Repository)



| A | | B | |
|----------------|----------------|----------------|----------------|
| X ₁ | X ₂ | X ₁ | X ₂ |
| -1.520 | -1.150 | 1.140 | -0.114 |
| -0.916 | 0.397 | -1.050 | 0.720 |
| -1.090 | 0.437 | 1.830 | 0.452 |
| -0.584 | 0.094 | 1.790 | -0.459 |
| -1.250 | -0.286 | -0.122 | -0.808 |
| 1.700 | 1.210 | -0.768 | -1.040 |
| -0.482 | -0.485 | 0.724 | 0.989 |
| 0.081 | 1.930 | 0.444 | 1.990 |
| -0.541 | -0.332 | -1.010 | -1.360 |
| -1.690 | -1.150 | 1.280 | 0.691 |
| 1.260 | 1.210 | 0.925 | 0.895 |
| -0.863 | 0.496 | -0.687 | -1.290 |
| 1.160 | 0.458 | 1.710 | -0.044 |
| -0.595 | -0.651 | 1.120 | 0.626 |
| -0.770 | 0.364 | 1.300 | 0.196 |
| -0.871 | -0.825 | 1.130 | 1.480 |
| 0.996 | -1.700 | 0.763 | 0.921 |
| 1.740 | 0.964 | -1.410 | 1.110 |
| 1.180 | -0.335 | -0.750 | -0.881 |
| 2.520 | 1.430 | 1.116 | 0.978 |
| 0.271 | -0.591 | 1.130 | 0.405 |
| -1.590 | -0.68 | -0.522 | -1.340 |
| 0.408 | 0.067 | -1.310 | 1.250 |
| 0.009 | -0.434 | 0.041 | -1.130 |
| -2.140 | -1.430 | 0.048 | 0.866 |
| 0.007 | 0.012 | -2.110 | 0.193 |
| -0.352 | -0.490 | 0.522 | 1.460 |
| 1.330 | 1.510 | 0.028 | 1.620 |
| 1.090 | -1.370 | 0.536 | 0.921 |
| -1.670 | -1.260 | -0.123 | -1.070 |
| -0.508 | -9.715 | 0.526 | 1.480 |

- Sort values in both of A and B respectively
- Divide these sorted values into 3 groups - large, medium & small
- Calculate avg & std of these 6 groups
- Draw Gaussian membership functions for each of these 6 groups
- Translate all numerical values into natural language: large, medium & small
- Create rules to classify data
- Then guess that the data [x₁ = -1.620 & x₂ = 0.468] is class A or B

Mammo graphic dataset

(extracted from UCI (University of California, Irvine)
Machine Learning Repository)

| Normal | | | | | Not normal | | | | |
|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| X ₁ | X ₂ | X ₃ | X ₄ | X ₅ | X ₁ | X ₂ | X ₃ | X ₄ | X ₅ |
| 5 | 57 | 3 | 5 | 3 | 4 | 28 | 1 | 1 | 3 |
| 5 | 58 | 4 | 5 | 3 | 4 | 36 | 3 | 1 | 2 |
| 5 | 57 | 1 | 5 | 3 | 4 | 60 | 2 | 1 | 2 |
| 5 | 76 | 1 | 4 | 3 | 4 | 54 | 1 | 1 | 3 |
| 3 | 42 | 2 | 1 | 3 | 3 | 52 | 3 | 4 | 3 |
| 4 | 59 | 2 | 1 | 3 | 5 | 86 | 4 | 4 | 3 |
| 4 | 54 | 1 | 1 | 3 | 5 | 66 | 4 | 4 | 4 |
| 5 | 56 | 4 | 3 | 1 | 5 | 60 | 3 | 1 | 3 |
| 5 | 42 | 4 | 4 | 3 | 3 | 45 | 2 | 1 | 3 |
| 4 | 59 | 2 | 4 | 3 | 3 | 43 | 2 | 1 | 3 |
| 5 | 75 | 6 | 5 | 3 | 2 | 49 | 2 | 1 | 3 |
| 6 | 71 | 4 | 4 | 3 | 4 | 47 | 3 | 1 | 3 |
| 5 | 62 | 3 | 5 | 2 | 4 | 24 | 2 | 1 | 3 |
| 5 | 80 | 3 | 5 | 3 | 6 | 41 | 2 | 1 | 3 |
| 5 | 74 | 1 | 1 | 2 | 4 | 19 | 1 | 1 | 3 |

- Sort values in both Normal and Not normal
- Divide these sorted values into 2 groups - Large & Small
- Calculate avg & std of these 10 groups
- Draw Gaussian membership functions of each of these 10 groups
- Translate all numerical values into Large or Small
- Create rules to classify data
- Then guess that data (4, 62, 3, 3, 3) is Normal or Not normal

X₁: BI-RADS, X₂: Age, X₃: Shape, X₄: Margin, X₅: Density