VICTORIA UNIVERSITY OF WELLINGTON
Te Whare Wananga o te Upoko o te Ika a Maui

School of Engineering and Computer Science

COMP 422

New GP Techniques for Classification

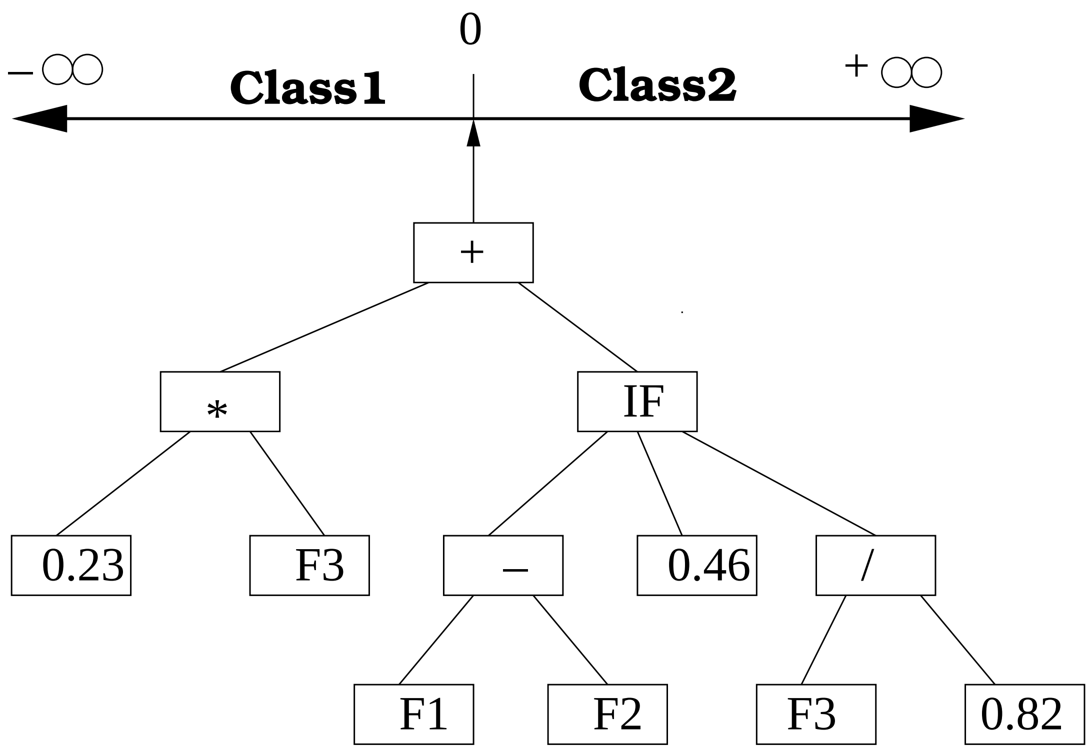
Mengjie Zhang

mengjie@ecs.vuw.ac.nz

Outline

- Structure of standard GP
- Binary classification
- Multiclass classification
  - Class translation from the program output
  - Multiple outputs
  - Probability based GP
- Object detection — Fitness function
- Search techniques
  - gradient descent on constants

Standard GP for Binary Classification

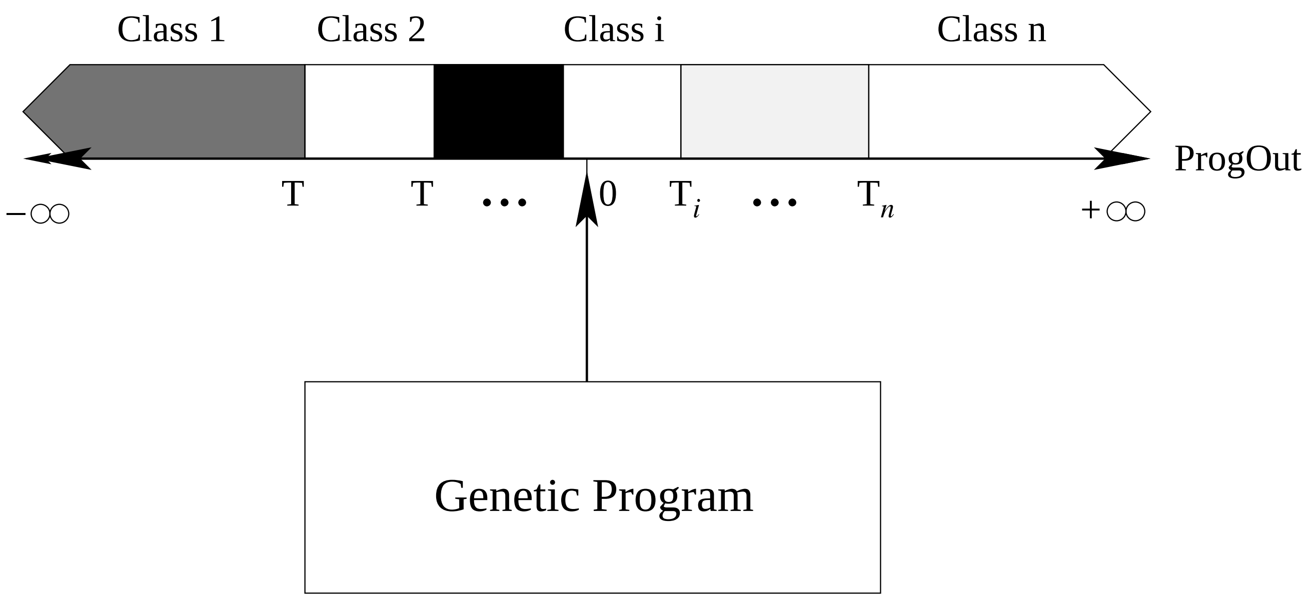



```
if ProgOut > 0  then  Class1;
                else  Class2;
```

Classification Map

Static Class Boundary Determination

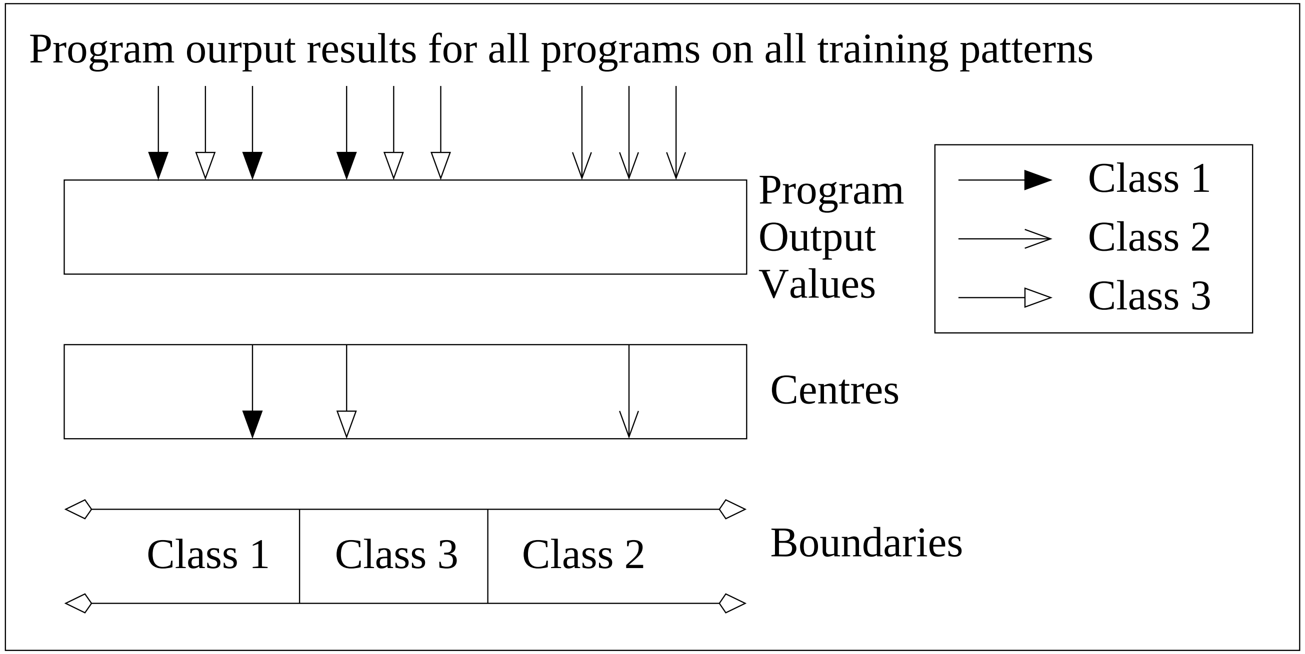
- Boundaries are **fixed** at locations on the real number line of the program output
- These boundaries are **predefined**
- A class is determined from the **fixed regions**
- Classes are in a **fixed** order



Dynamic Class Translation

Centred Dynamic Class Boundary Determination

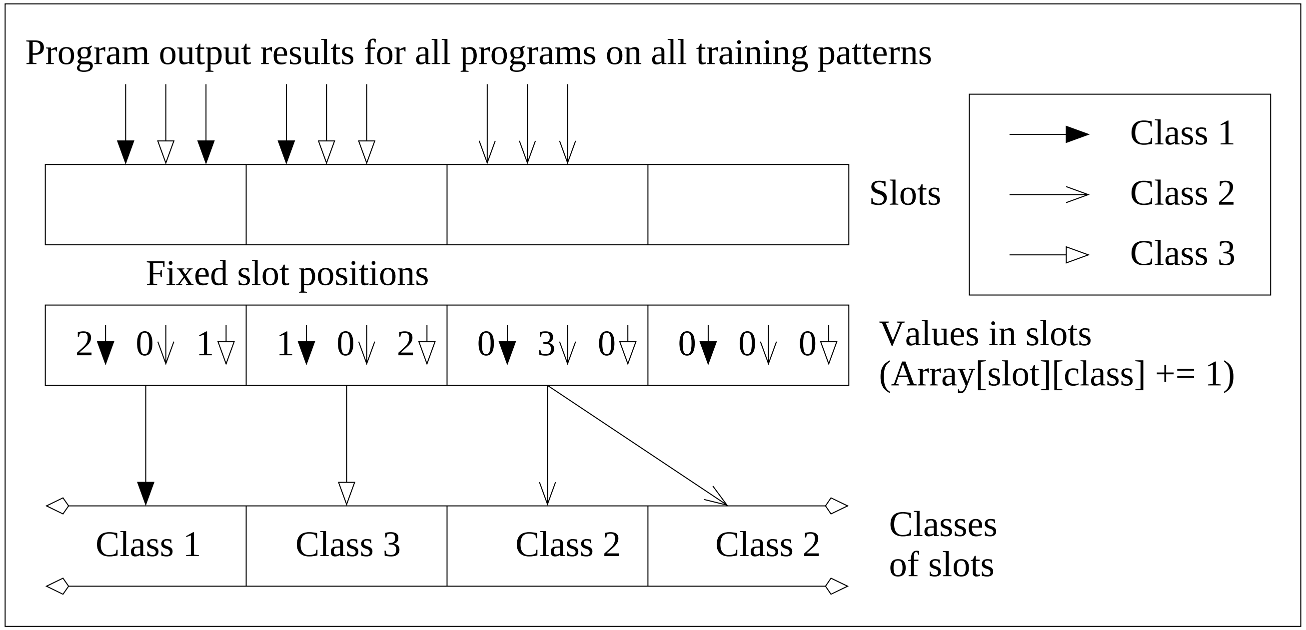
- Boundaries are **dynamically** determined based on the **centres** of different classes, each of which is calculated as the average output of all the programs for training examples of that class.
- Boundaries are set **halfway between adjacent centres**.



Dynamic Class Translation

Slotted Dynamic Class Boundary Determination

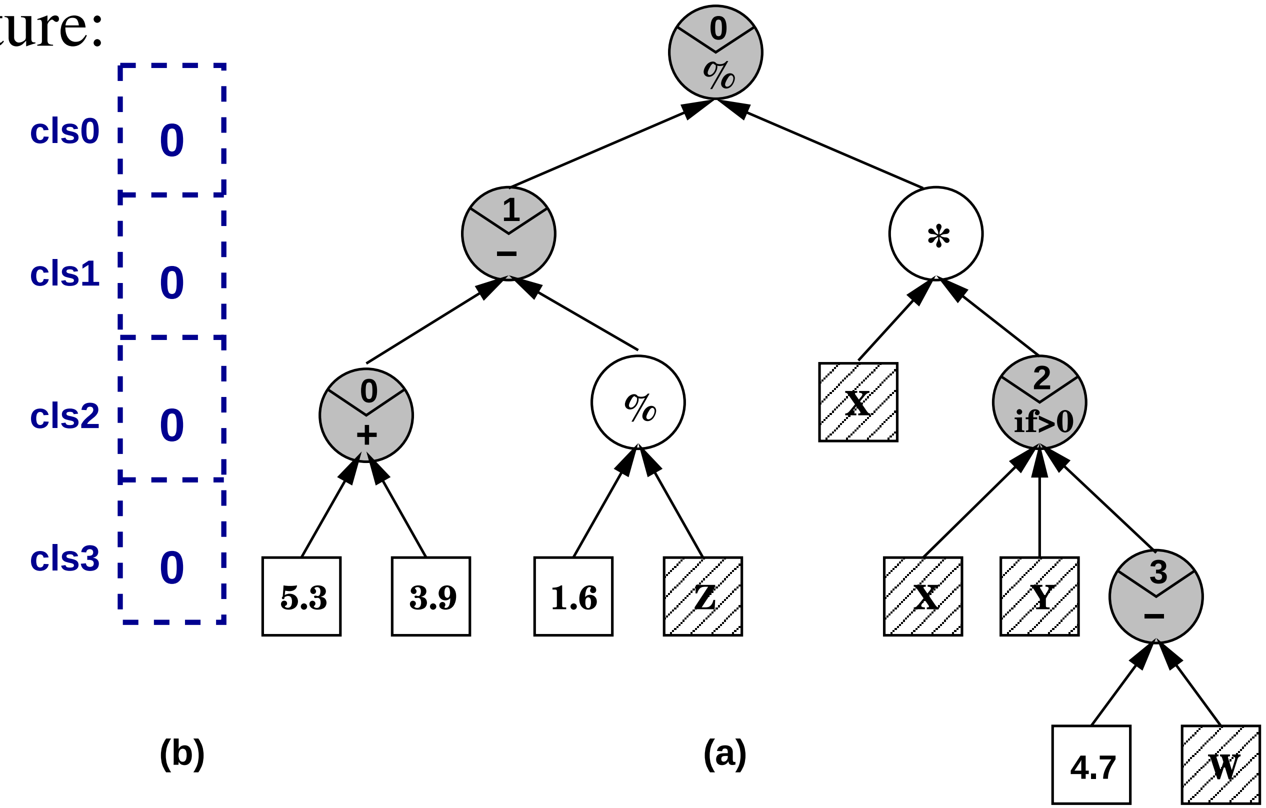
- Real number line divided into 200 **slots** in [-25, 25]
- Slots are assigned the class labels during evolution
  - the class with **the most** programs that fall into the slot.



Multiple Outputs

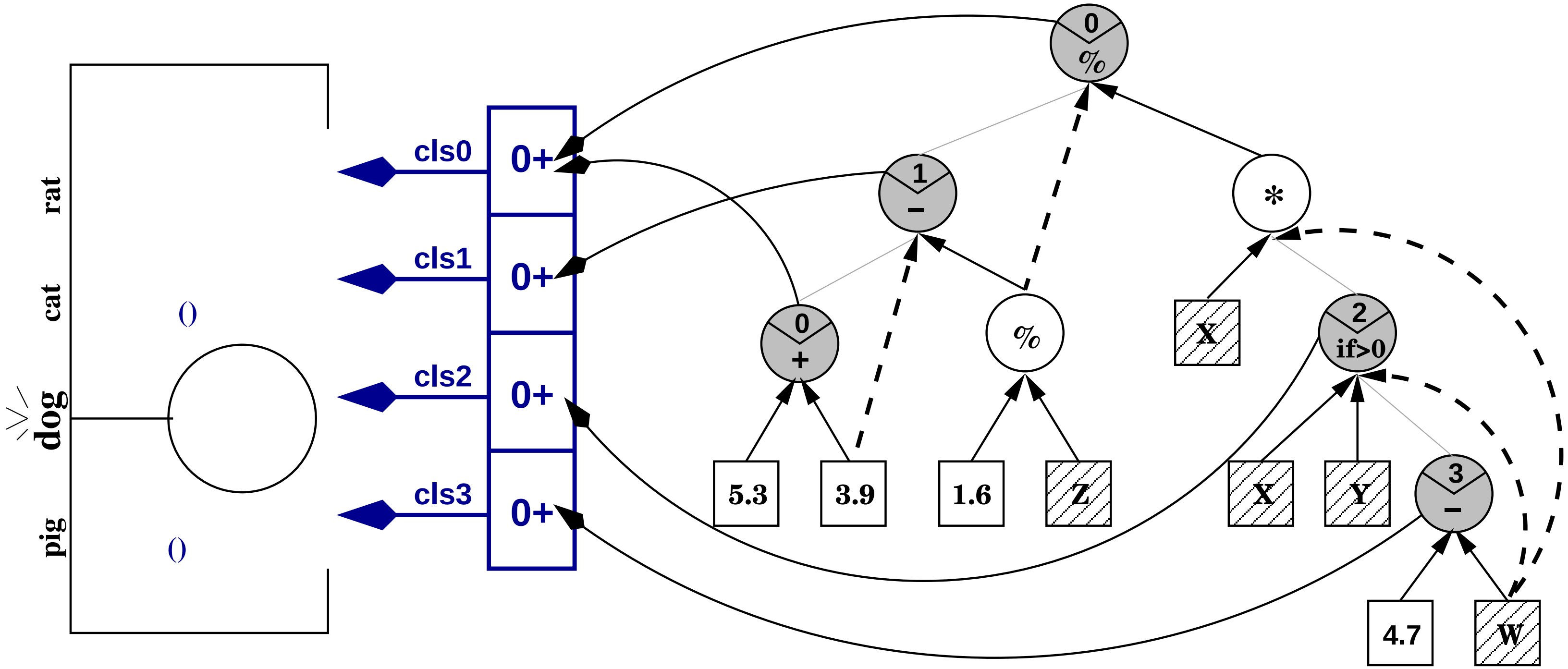
Program Structure

- A genetic program can produce more than one output value, each for a class
- A voting strategy (WTA) is applied
- Program Structure:



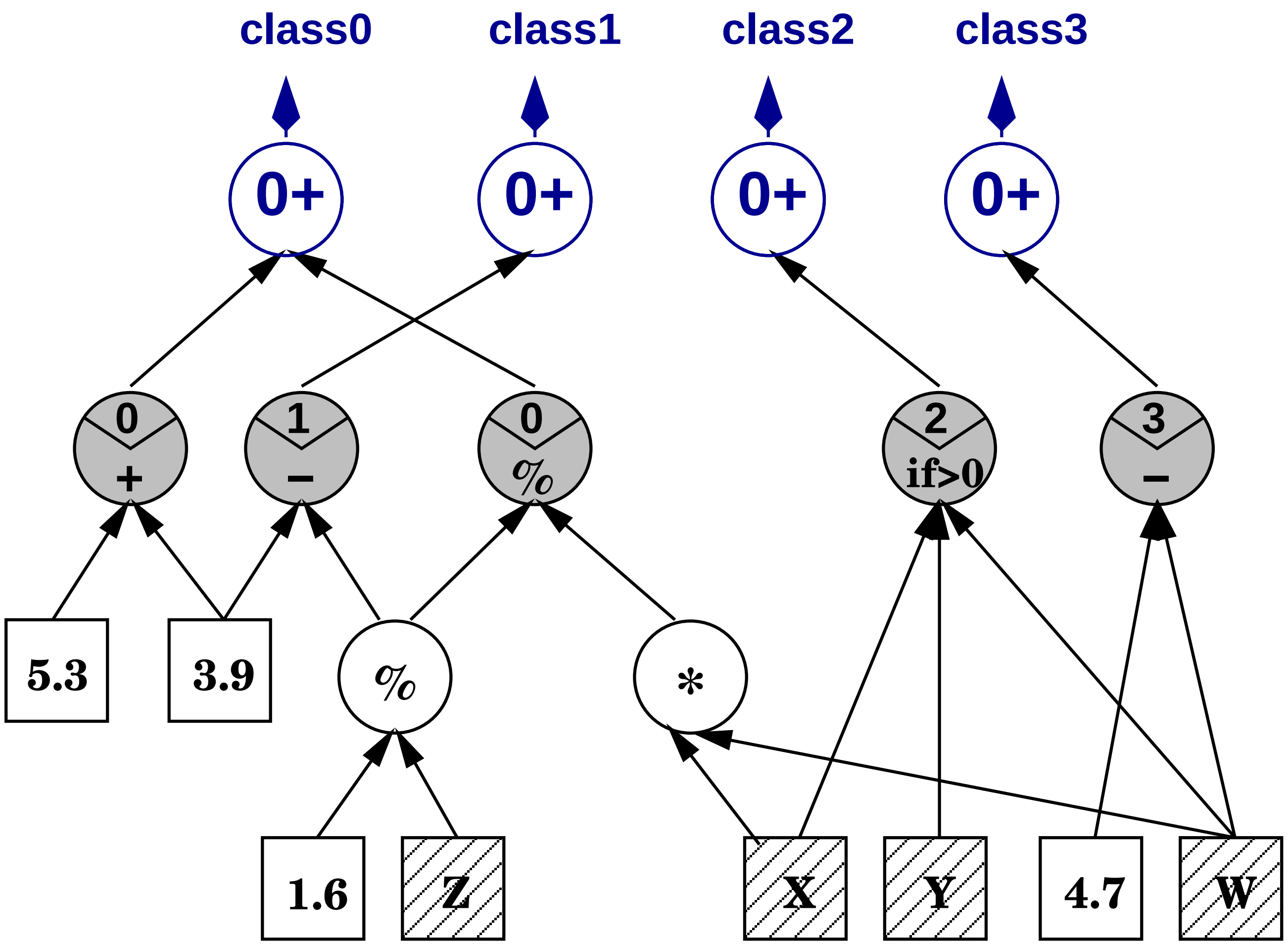
Multiple Outputs

- Program Evaluation



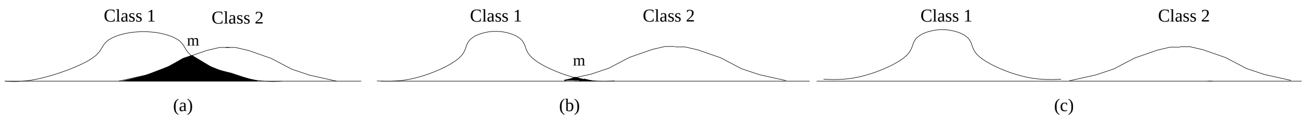
Multiple Outputs

- Program Simulation



Probability GP

- Fitness function: replace classification accuracy with probability
- Fitness Measures: area vs distance



- Area Measure:

$$P(x) = \frac{\exp(\frac{-x^2}{2})}{\sqrt{2\pi}} \qquad A(x) = \Sigma_{i=0}^{\frac{x}{\alpha}} \alpha P(\alpha i)$$

$$A(\mu, \sigma, x) = A(\frac{x - \mu}{\sigma})$$

$$A_o = 1 - A(\mu_1, \sigma_1, m) - A(\mu_2, \sigma_2, m)$$

Probability GP (Continued)

- Distance measure: weighted distribution distance $d = 2 \times \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2}$
- Standardised distribution distance measure $d_s = \frac{1}{1+d}$
- Fitness function:

$$fitness = \sum_{i=1}^{C_n^2} M_i$$

- Classification with multiple programs:

$$Prob_c = \prod_{i=1}^{l} P(\mu_{i,c}, \sigma_{i,c}, r_i)$$

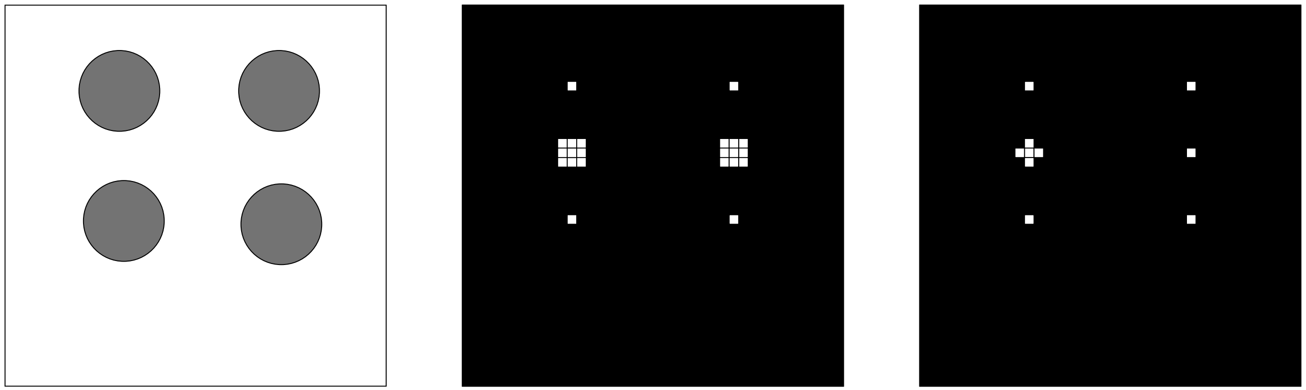
$$P(\mu, \sigma, x) = \frac{\exp(\frac{-(x-\mu)^2}{2\sigma^2})}{\sigma\sqrt{2\pi}}$$

Object Detection — Fitness Function

- Fitness function is based on detection rate and false alarm rate:

  $fitness(DR, FAR) = W_d * (1 - DR) + W_f * FAR$

- One problem: could not reflect the small improvement



(a) (b) (c)

- Second problem: programs are often very long

- A new fitness function:

  $fit = K_1 \cdot (1 - DR) + K_2 \cdot FAR + K_3 \cdot FAA + K_4 \cdot ProgSize$

- Research question: how to set parameter K_i

Gradient Descent in GP

- Gradient descent search/hill climbing search is widely used in many techniques, including neural networks.
- Gradient descent search has two "problems":
  – one run only has one potential solution;
  – it often has the local minuma.
- Gradient descent search can use the heuristics; local minuma is not the ideal/best solution, but often meets the requirements of many applications.
- Genetic beam search can solve/improve the local mimuma problem, but it does not use the heuristic sufficiently.
- Can we combine them together?

Gradient Descent in GP

- Apply gradient descent locally on the **numeric terminals**

$$\Delta O_i = -\alpha \cdot \frac{\partial C}{\partial O_i} = -\alpha \cdot \frac{\partial C}{\partial y} \cdot \frac{\partial y}{\partial O_i}$$

$$C = \frac{(y - Y)^2}{2}$$

$$\frac{\partial C}{\partial y} = \frac{\partial(\frac{(y-Y)^2}{2})}{\partial y} = y - Y$$

$$Y = \mathbf{class} - \frac{\mathbf{numclass} + 1}{2}$$

Gradient Descent in GP

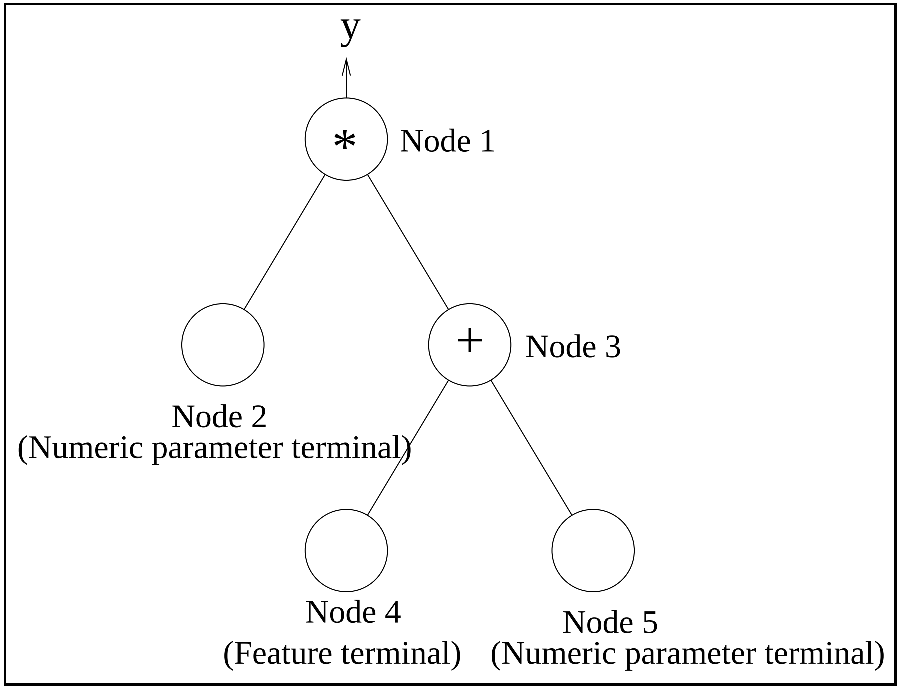
Function f	meanings	$\frac{\partial f}{\partial a_1}$	$\frac{\partial f}{\partial a_2}$	$\frac{\partial f}{\partial a_3}$
(+ a_1 a_2)	$a_1 + a_2$	1	1	–
(- a_1 a_2)	$a_1 - a_2$	1	-1	–
(* a_1 a_2)	$a_1 \times a_2$	a_2	a_1	–
(/ a_1 a_2)	$a_1 \div a_2$	a_2^{-1}	$-a_1 \times a_2^{-2}$	–
(if a_1 a_2 a_3)	if $a_1 < 0$ then a_2 else a_3	0 0	1 if $a_1 < 0$ 0 if $a_1 \geq 0$	0 if $a_1 < 0$ 1 if $a_1 \geq 0$

$$\frac{\partial y}{\partial O_2} = \frac{\partial (O_2 O_3)}{\partial O_2} = O_3$$

$$\frac{\partial y}{\partial O_5} = \frac{\partial (O_2 O_3)}{\partial O_5} = \frac{\partial (O_2 O_3)}{\partial O_3} \cdot \frac{\partial O_3}{\partial O_5}$$

$$= \frac{\partial (O_2 O_3)}{\partial O_3} \cdot \frac{\partial (O_4 + O_5)}{\partial O_5}$$

$$= O_2 \cdot 1 = O_2$$



Gradient Descent in GP

$$\alpha = \eta \cdot \frac{1}{\sum_i^N (\frac{\partial y}{\partial O_i})^2}$$

- New value of the Numeric terminal

$$(O_i)_{new} = O_i + \Delta O_i = O_i - \eta \cdot \frac{1}{\sum_i^N (\frac{\partial y}{\partial O_i})^2} \cdot \frac{\partial C}{\partial O_i}$$

- This algorithm is only **locally** applied to individual programs.
- Genetic beam search is still **globally** applied to the evolutionary process.
- online learning vs offline learning
- every generation vs every five generations