VICTORIA UNIVERSITY OF WELLINGTON

Te Whare Wananga o te Upoko o te Ika a Maui

School of Engineering and Computer Science

COMP 307 — Lecture 12

Evolutionary Computing 3 (ML 9)

GP for Symbolic Regression and Classification

Dr Bing Xue (Prof. Mengjie Zhang)

Bing.xue@ecs.vuw.ac.nz

Outline

- Statistical parameter regression
- Symbolic regression
- GP for symbolic regression
- GP for binary classification

Regression

Year	Winner	Incumbent	Probability Incumbent Wins
1936	Franklin Roosevelt	Won	0.999888
1864	Abraham Lincoln	Won	0.99967
1956	Dwight Eisenhower	Won	0.998827
1996	William Clinton	Won	0.996879
1924	Calvin Coolidge	Won	0.975284
1984	Ronald Reagan	Won	0.969
1916	Woodrow Wilson	Won	0.951723
2012	?	Obama?	0.948372
1964	Lyndon Johnson	Won	0.877104
1944	Franklin Roosevelt	Won	0.868832
1992	William Clinton	Lost	0.853392

- y: probability of one win in the presidential election
- x: a stock market data (feature/attribute)
- Used previous years examples to find the relationship between x and y: $\boxed{y = x^2 + e^x - 0.1234 * x}$
- Given the x value for Obama, to calculate the y value — the probability of Obama being the president in 2012.

Regression

Year	Winner	Incumbent	Probability Incumbent Wins
1936	Franklin Roosevelt	Won	0.999888
1864	Abraham Lincoln	Won	0.99967
1956	Dwight Eisenhower	Won	0.998827
1996	William Clinton	Won	0.996879
1924	Calvin Coolidge	Won	0.975284
1984	Ronald Reagan	Won	0.969
1916	Woodrow Wilson	Won	0.951723
2012	?	Obama?	0.948372
1964	Lyndon Johnson	Won	0.877104
1944	Franklin Roosevelt	Won	0.868832

If you are interested, check:
http://blog.minitab.com/blog/adventures-in-statistics/predicting-the-us-presidential-election-evaluating-two-models-part-one

1828	Andrew Jackson	Lost	0.18699
1840	William Harrison	Lost	0.094275
1932	Franklin Roosevelt	Lost	0.000443

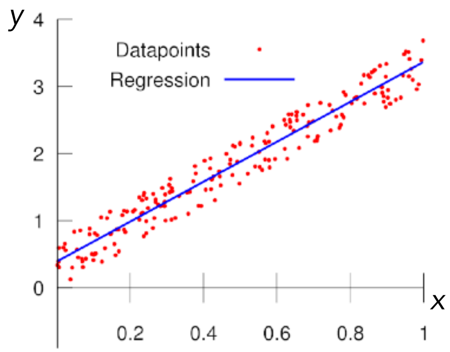
(*Statistical*) Regression Analysis

- In statistics, regression analysis examines the relation of a dependent variable (response variable) to specified independent variables (explanatory variables)
  - The *mathematical model* of their relationship is the *regression equation*
  - *estimates of one or more hypothesized regression parameters ("constants")*
- Allow predicting the value of the dependent variable for given value(s) of independent variable(s)
- e.g. *curve fitting, prediction, modelling of causal relationships, and testing scientific hypotheses about relationships between variables*

(*Statistical*) Regression Analysis

- Process
  - Given data points
  - Assume linear model
  - Equation:
    $$y = \alpha + \beta x + \epsilon$$
  - α is the intercept
  - β is the slop
  - ϵ is the error term
  - The error term is usually taken to be normally distributed
  - Use some methods to estimate α and β

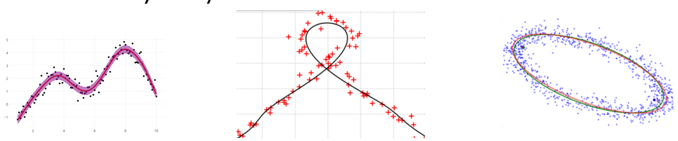
Simple Linear Regression



Assume model structure, estimate model parameters

Symbolic Regression

- Problems of statistical (parameter) regression
  - Need domain expertise to assume certain distribution of the given data, which is usually unknown in advance
  - Need statistical expertise to find an "appropriate" model, which is usually very hard



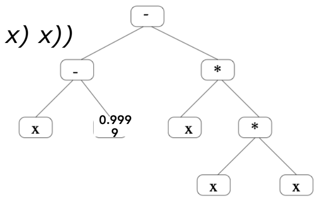
- Symbolic regression: the object to be found is a symbolic description of a model, not just a set of coefficients/parameters in a pre-specified model.
- To find both:
  - the model structure, and
  - the corresponding coefficients/parameters

GP for Symbolic Regression

- Objective: Find a program/model that produces the correct value of the dependent variable y when given the value of independent variable x
- Terminal Set: *x* and random number *r*
- Function Set: {+ , -, *, %}
- Fitness Cases: 50 cases of *x* and the corresponding *y* values (e.g. *50 instances/patterns/cases*)
- Fitness Measure: Sum of the *absolute* errors for the 50 cases
- Parameters: Population = 100. Generations = 51, ProgSize = 6? reproduction rate: 5%, crossover rate: 90%, mutation rate: 5%
- Success: The fitness value is smaller than a pre-defined value, e.g. 0.55
- Termination criteria: satisfactory solutions found, or at generation 51.

GP for Symbolic Regression

- One GP run gave: $y = (x - 0.9999) - x^3$
  which can be written as *(- (x-0.9999) (*(* x x) x))*
  - Successful ? if the "*true*" model is
  - $y = (x - 1) - x^3$



- Sometimes:
  (% (% (* (* X 0.571) (* (- (* (+ (% 0.634094 0.68469) (+ (+ X X) -0.5992))(* (* (+ (% 0.634094 0.68469) (+ X -0.5992)) (* (% 0.354904 - 0.7549) (* X 0.571))) (- X 0.395493))) - 0.4665) ....another 15 lines)

- This example: one input variable (x), training set only
- Real-world applications: usually multiple variables, can have a separate test set, but use the same principle

GP for Symbolic Regression Problems: Properties

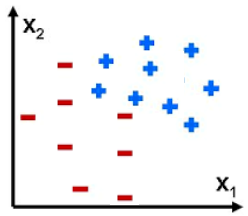
- Compared with statistical parameter regression methods, GP method has the following properties:
  - Does NOT need to assume any distribution of data set,
  - Does NOT need to assume the independence of the input variables
  - Does NOT need to use any statistical background knowledge to assume any model
  - Can automatically learn/***evolve*** both the model structure and the model parameters at the same time!
  - System input: *just the data* with a black box model/parameters
  - System output: a white box *model structure* with appropriate *parameters*!

GP for Symbolic Regression Applications

- GP for symbolic regression has many real-world applications, including:
  - Economic prediction, e.g. stock market prediction, GDP prediction,
  - Industrial prediction, e.g. prediction of containers handling capacity at a particular sea port; short-term, medium-term and long-term prediction of power load at a region
  - Experiential formula modelling in Engineering, e.g. formulating the amount of Gas emitted from Coal surface
  - Time series projection, e.g. CPI projection for a country or a region
  - Selection/Choice of Equipments, e.g. equipment choice for work platform in mine industry
  - Fault diagnosis, e.g. find optimal strategy in fault isolation, fault analysis in combustion system for diesel engine
  - Robot self-adaptive behaviour
  - GIS systems, e.g. projection transformation

Binary Classification

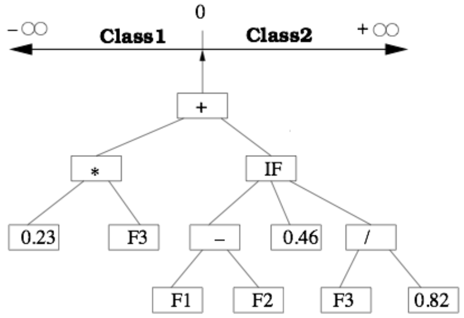
- Binary classification is the task of classifying the instances of a given set into two categories on the basis of whether they have some property or not
- Two target classes, e.g.
  – Disease vs non-disease
  – normal vs abnormal
  – grant loan or not
  – fault vs non-fault/normal
  – X vs O
  – object vs non-object



GP for Binary Classification

- Compared with GP for symbolic regression problems, the terminal set and function set can be the same or very similar, but the fitness function is normally very different
- In fitness function, we can simply use classification accuracy or error rate, which need to determine which class a training example belongs to
- This is called Classification Strategy or Program Class Translation Rule
- For binary classification problems, this is quite easy: we can use the value "zero" in the real number space for the program output to separate the two classes

GP for BC — Program Class Translation Rule




```
Genetic Program: (+ (* 0.23 F3)
                    (IF (- F1 F2) 0.46 (/ F3 0.82))
                 )
```

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


GP for Classification Example

- Task: Object classification: *objects vs non-objects*
- Objective: Find a program which can successfully *split* the instances into *two* classes
- Terminal Set: Object *attributes*: pixels, pixel statistics, or specific features, and *random numbers*.
- Function Set: {+ , -, *, %, ABS, EXP, LOG, SIN, COS, RAND}
- Fitness Cases: Build a training set of *patterns* (*feature vectors*), some are objects, some not.
- Fitness Measure: classification accuracy/ error rate
- Classification strategy: ProgOut > 0 for objects, otherwise non-objects
- Parameters: Population = 200? Generations = 50? Crossover rate =? Mutation rate = ? Program size =?

Basic GP Algorithm

This GP algorithm is based on the proportional selection model

1. Initialise the population
2. Evaluate the fitness of each individual program in the current population.
3. Until the new population is fully created, repeat the following:
   - Select programs in the current generation.
   - Perform genetic operators on the selected programs.
   - Insert the result of the genetic operations into the new generation.
4. If the termination criterion is not fulfilled, repeat steps 2-4 with the new generation.
5. Present the best individual in the population as the output.

Tackling a Problem with GP

- What is the set of terminals used in the program trees?
- What kind of functions can be used to form the function set to represent the program tree?
- What is the fitness measure?
- What values can be given for the parameters and variables for controlling the evolutionary process, for example, population size and number of generations?
- When to terminate a run?
- How do we know the result is good enough?
- What genetic operators, at what frequencies, are going to be applied?

Summary

- GP for symbolic regression
- Properties of GP for symbolic regression
- GP for binary classification

- How do you use GP for multi-class classification? Can we get better translation rules? COMP422

- Next Lectures: Quantifying uncertainty and probabilistic reasoning