Automatic Synthesis of Branch Prediction Schemes through Genetic Programming

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Short Presentation

Started in 1998 like a small **research group**.
Now we are a **Research&Development company** with German capital.
Our **main products** are
Search Engine Agents (http://airg.verena.ro/sea)
Product Knowledge Management (http://www.wittmann-edv.de)
Also we are involved in some **research projects** like RoboCup simulation league.
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Overview

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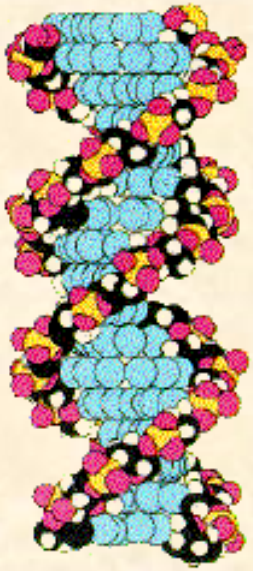
1. Motivation

Predictors (scheme) made by human



Predictors (scheme) “Dolly”

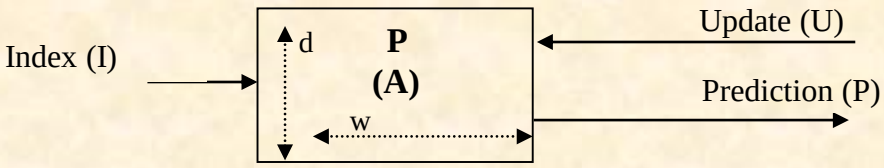
An integrated approach in Computer Architectures

2. Current trends

- ✓ Branch Target Buffer (BTB) structures
- ✓ Two Level Adaptive Branch Prediction
  - ➢ History Register (HR)
  - ➢ Pattern History Table (PHT)
- ✓ Neural branch prediction
- ✓ Markov chains predictors
- ✓ Automatic Synthesis of Branch Prediction Schemes

3. BPL Introduction

Memory Structure



Name	Description	Type
w	Width	Static
d	Depth	Static
i	Index for prediction and update	Dynamic
u	Update value	Dynamic

Language Terminals

Terminal Name	Description
T	Taken/Not Taken value read from trace file (1 bit value)
PC	Current program counter
A	Refer first A type memory definition
P	Refer first P type memory definition
0	0
1	1

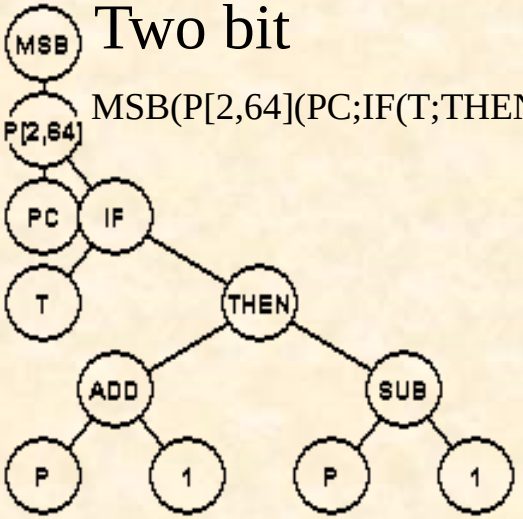
4. BPL Functions

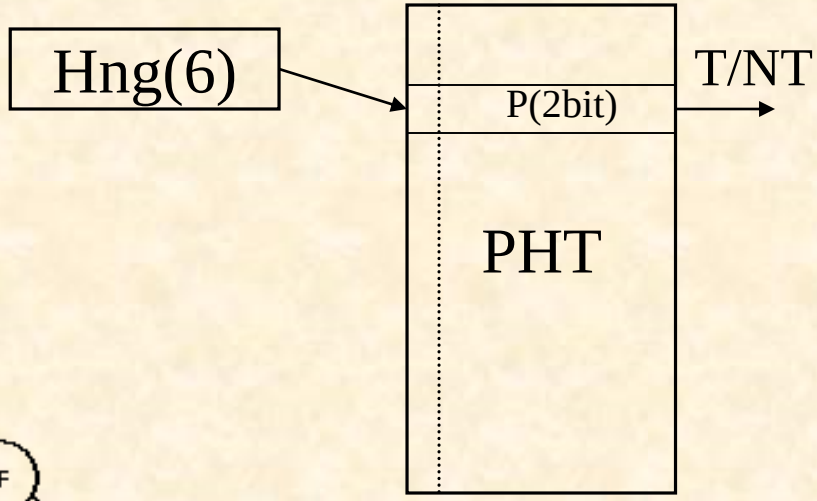
Functions	Description
MSB	Most significant bits
CAT	Concatenation
XOR	Xor function
MASKHI	Most n significant bits
MASKLO	Most less n significant bits
SUB	Saturating subtraction (0 val. min)
ADD	Saturation adding
EQU	Equality of two values
IF	If
THEN	Then
PLUS	Adding
MINUS	Subtraction

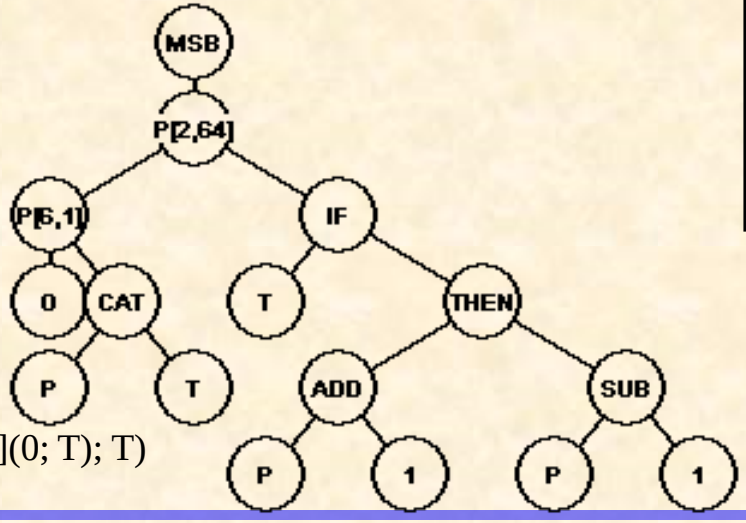
5. Predictors samples

Two bit

MSB(P[2,64](PC;IF(T;THEN(ADD(P;1);SUB(P;1)))))







GAg

Gag[n](; T) = Twobit[2^n](Hist[n,1](0; T); T)

6. Genetic Algorithm

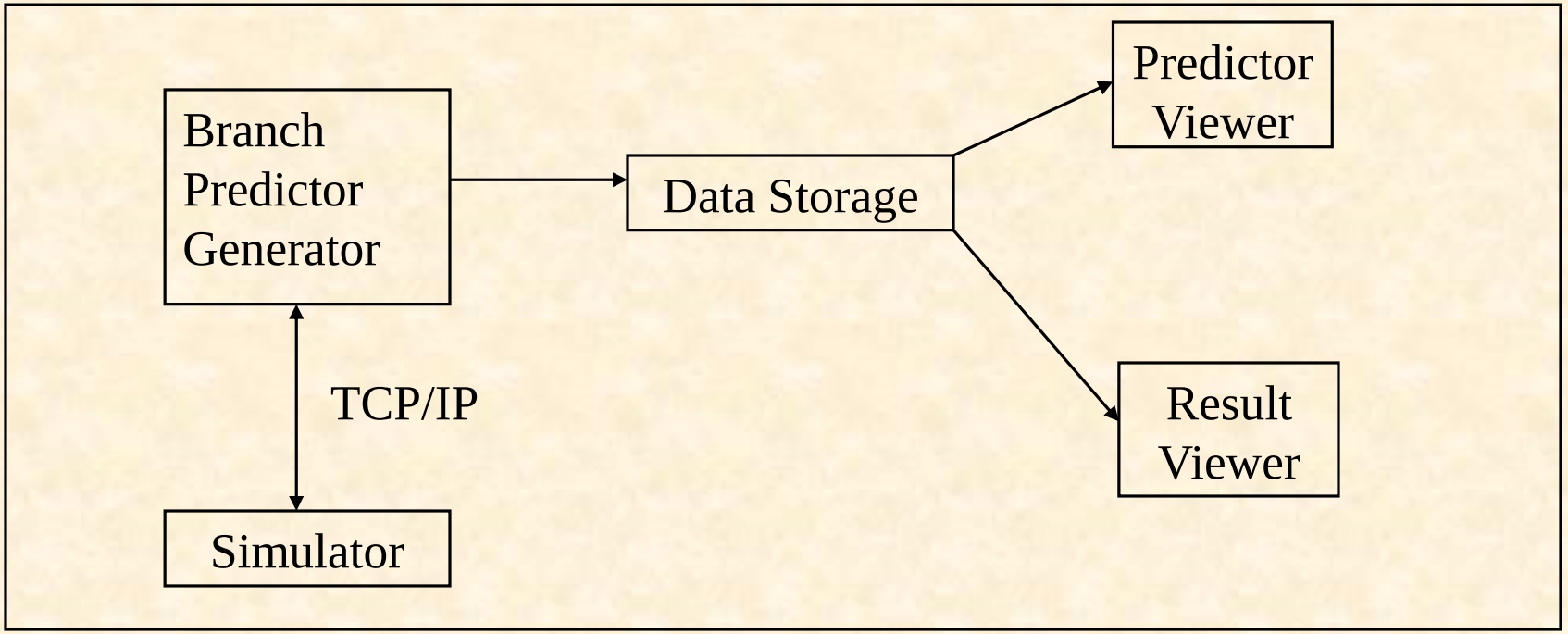
Algorithm steps

- 1. Create initial population of randomly generated individuals
- 2. Rank fitness of individuals in the population by simulation
- 3. Apply genetic operations to create new generation
- 4. If no stop condition (e.g. if user send a stop command) go to step 2

Genetic operators

- Integrity check
- Replication
- Crossover
- Mutation

7. System architecture



General System Structure

8. Implementation

Cluster used for simulations

5 Computers PIII 500Mhz
196 MB RAM
5Gb HDD
Windows 2000

- 1 Server
- 4 Clients

- Simulate for maximum 5 generation
- Each population has 400 chromosomes
- Simulation time for 1 generation is 60 seconds
  - 60 seconds * 400 chromosomes => 400 min ~ 6.6 hours * 5 generation ~ 33.3 hours ~ 1.4 days

9. Experimental results

Predictor	Rate
Onebit[1,2K]	0.664
Twobit[2,64K]	0.746
Gag[2]	0.849
Pag[18,8K]	0.825
Pap[9,18,8K]	0.771

Predictor	Rate
MSB(MASKHI(ADD(A[23,64](0;T);A[1,128](PC;PC));0))	0.711
MSB(EQU(MSB(MASKHI(ADD(IF(XOR(0;1);THEN(PC;PC));SUB(MSB(A[22,64](1;1));MASKLO(0;EQU(PC;PC))));PC));0))	0.759
MSB(EQU(XOR(SUB(MINUS(0;1);IF(ADD(A[31,64](A;PC);1);THEN(1;PC)));EQU(PC;PC));ADD(A[24,32](0;1);MASKHI(MSB(1);PC))))	0.811

For simulation we use the Stanford traces

10. Conclusions and future work

- Can describe a variety of predictors, also manipulate them very easy
- Predictor obtained automatically are comparable with the “hand made”
- Are too complex
- Some interesting new ideas useful in human designed branch predictors

- Extend the language with other components
- Adapt current version in order to find indirect jumps predictors
- Adding other genetic operators
- Algorithm for reduce the branch complexity

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