Effective Searching for Profitable Forex Trading Rules via Genetic Programming

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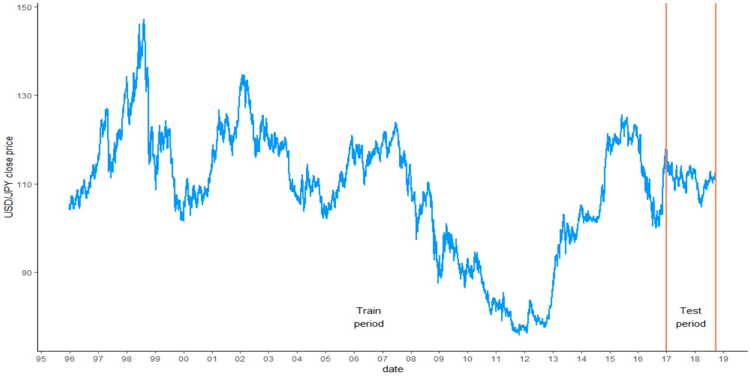
Research Question

- Can we let the machine to learn strategies from the exchange rate data (e.g. USD/JPY)?



Genetic Programming

Economics and Econometrics applications

1. Efficient market hypothesis validation
2. Portfolio optimisation
3. Option pricing
4. Risk analysis
5. Causal effects analysis

The Algorithm

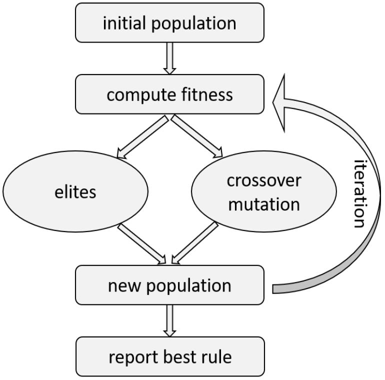


Figure: GP Algorithm(source:[6])

GP building blocks

1. Population
2. Fitness function
3. Evolution functions
   1. Crossover
   2. Mutation
   3. Elitism

Population: Tree-structured trading strategies

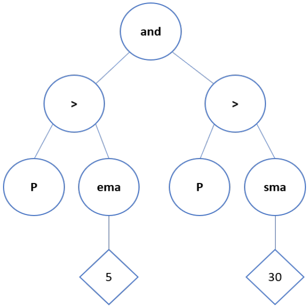


Figure: A long rule sample

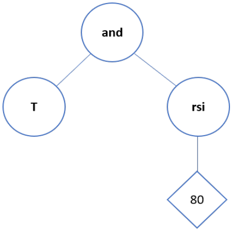


Figure: A short rule sample

Evolution: crossover

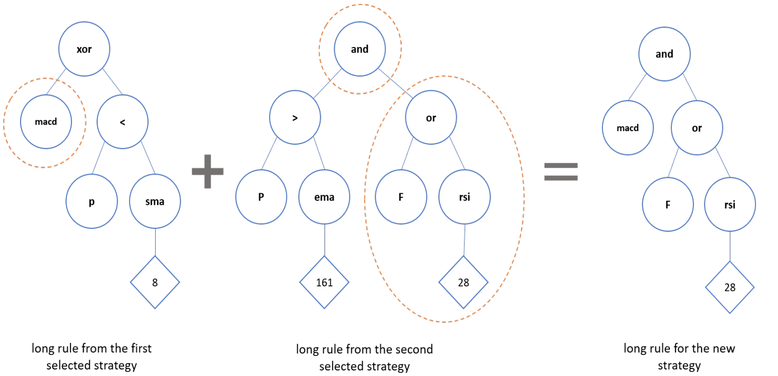


Figure: Crossover for long rules from two selected strategies

Evolution: mutation

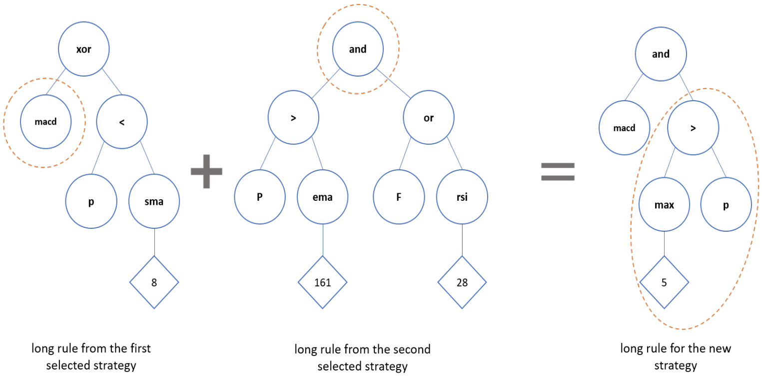


Figure: Mutation for long rules from two selected strategies

GP hyper-parameters

- The hyper-parameters of GP are

hyper-parameter	notation	value
population for each trial	n	30
iteration for each trial	η	20
maximum depth of trees	γ	10
elite ratio	e	10%
elite size	n*e	2
mutation rate	m	5%

- One trial: use GP to iterate one randomly generated population, take the best one in the last generation as the candidate solution. The process is called one trial.
- Repeat the trial for 10,000 times, obtain 10,000 candidate strategies.

Parallel computing in R

- Each trial is independent, i.e. opportunity for parallel computing.
- Given a powerful computer with 32 processors, one can open 30 R at the same time and each R runs for 333 trials.

```
Current generation period:  2 , Max fitness:  110.4113 Time consumption:  2.932164
Current generation period:  3 , Max fitness:  110.4113 Time consumption:  3.498654
Current generation period:  4 , Max fitness:  130.7968 Time consumption:  3.854699
Current generation period:  5 , Max fitness:  130.7968 Time consumption:  4.093063
Current generation period:  6 , Max fitness:  130.7968 Time consumption:  4.077104
Current generation period:  7 , Max fitness:  130.7968 Time consumption:  4.736344
Current generation period:  8 , Max fitness:  130.7968 Time consumption:  5.405556
Current generation period:  9 , Max fitness:  130.7968 Time consumption:  5.817457
Current generation period:  10 , Max fitness:  130.7968 Time consumption:  6.304155
Current generation period:  11 , Max fitness:  170.5584 Time consumption:  5.950101
Current generation period:  12 , Max fitness:  170.5584 Time consumption:  5.867323
Current generation period:  13 , Max fitness:  170.5584 Time consumption:  5.455423
Current generation period:  14 , Max fitness:  170.5584 Time consumption:  5.689796
Current generation period:  15 , Max fitness:  170.5584 Time consumption:  5.404563
Current generation period:  16 , Max fitness:  170.5584 Time consumption:  5.430489
Current generation period:  17 , Max fitness:  170.5584 Time consumption:  5.717721
Current generation period:  18 , Max fitness:  170.5584 Time consumption:  5.832417
Current generation period:  19 , Max fitness:  170.5584 Time consumption:  5.630953
Current generation period:  20 , Max fitness:  170.5584 Time consumption:  5.228031
Trial 352:, Max accumulated principal: 170.558361812492, Time consumption: 1.6706359

-----------------------first stage train-----------------------------------------
Trial 353:
```

A new two-phase searching method

The conjecture

Among 2000 trading strategy candidate, there may be better match-up of long and short rules. For one strategy's long rule, there might be a better short rule match-up from another strategy within 2000 candidates.

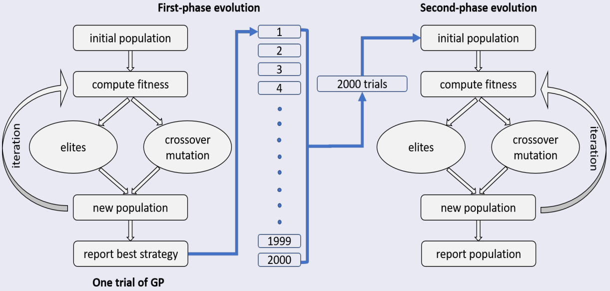
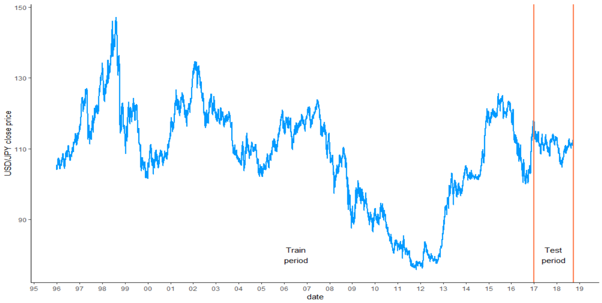


Figure: Two-phase searching method

Forex data



- Use daily JPY/USD exchange rate.
- Train period: 1996-01-01/2016-12-31, test period: 2017-01-01/2018-09-26
- Downloaded from Meta Trader 4, a popular platform among individual traders.

Performance summary

Test period performance of all 10 thousand, top 20, top 5 and the best strategy selected in the training period.

cumulative return (%)	train period		test period	
strategies:	1st phase	2nd phase	1st phase	2nd phase
all 10,000	230.3	506.5	100.3	94.4
top 20	520.3	1119.3	102.6	85.1
top 5	563.7	1122.0	105.0	84.0
top 1	582.0	1126.9	101.6	80.2

Table: Summary of average cumulative returns (%)

Test period performance visualisation

Extensions and Limitations

- Extensions for performance improvement
  1. Include more functions
  2. Fine-tune hyper-parameters
  3. Change data frequency
  4. Increase population size
- Limitation of the research
  1. No optimalisation theory is explained
  2. Searching space is small compares to existing literature.

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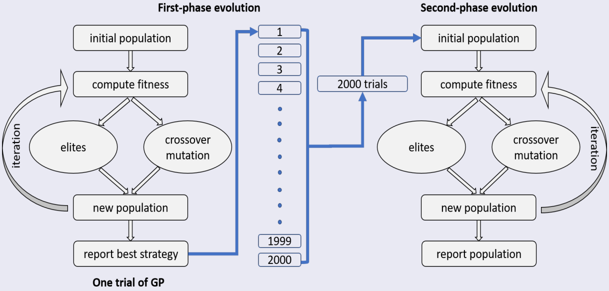

Figure: Two-phase searching method

A new two-phase searching method

- Summary of second-phase GP hyper-parameters

hyper-parameter	notation	value
population size	x	2000
iteration	η	10
elite ratio	e	1%
elite size	x*e	20
mutation rate	m	5%

Table: Summary of GP hyper-parameters in second-phase evolution

Second-phase searching performance boost