Predicting the Stock Market with Genetic Programming

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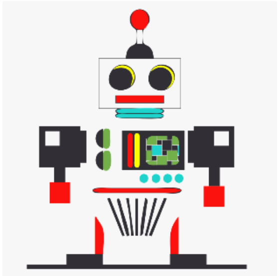

Data Scientists in ~~Stamford~~ Westport

January 25, 2016

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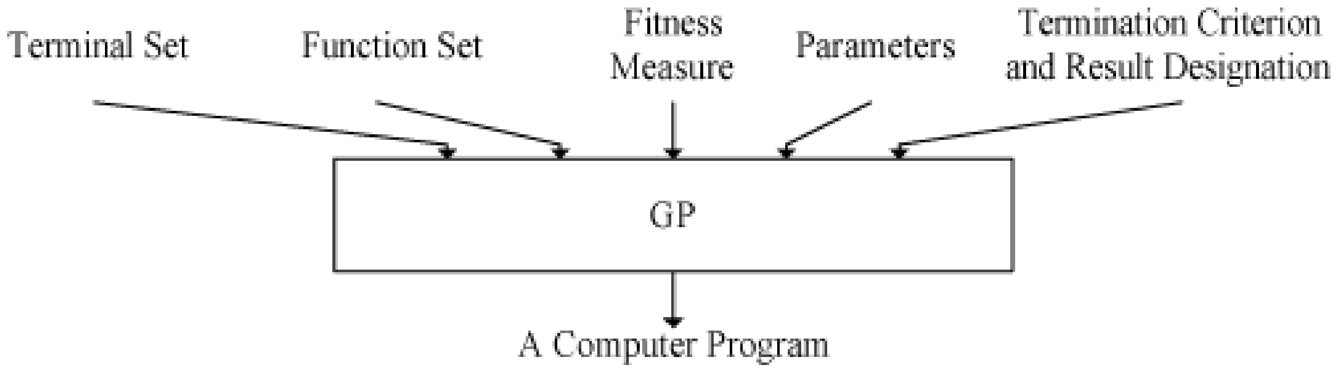
Agenda

- What is Genetic Programming?
- Time Series Prediction
- Stock Market Prediction
- Other Issues
  - Modularity
  - Linear GP
  - Genetic Algorithms
- Demonstrations

What is Genetic Programming?

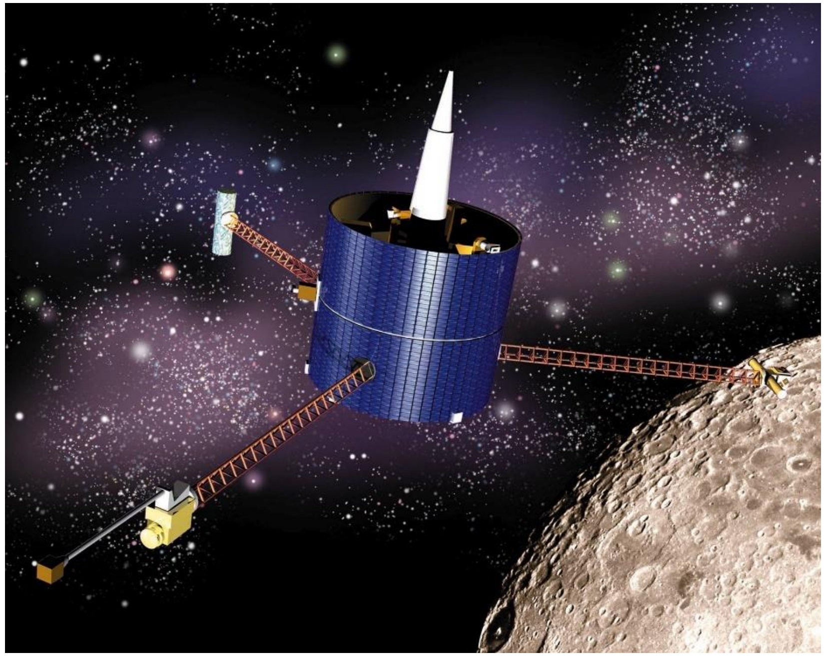
- Get a computer to do something without telling it how to do it
- Breeds a population of computer programs that improve over time
- Evolution
  - Genetic Operators
  - Survival of the Fittest
- Stochastic component
  - Non-Greedy
  - Creativity
  - Novel solutions
- Size and shape of solution unknown
- Limited only by what can be represented as a computer program

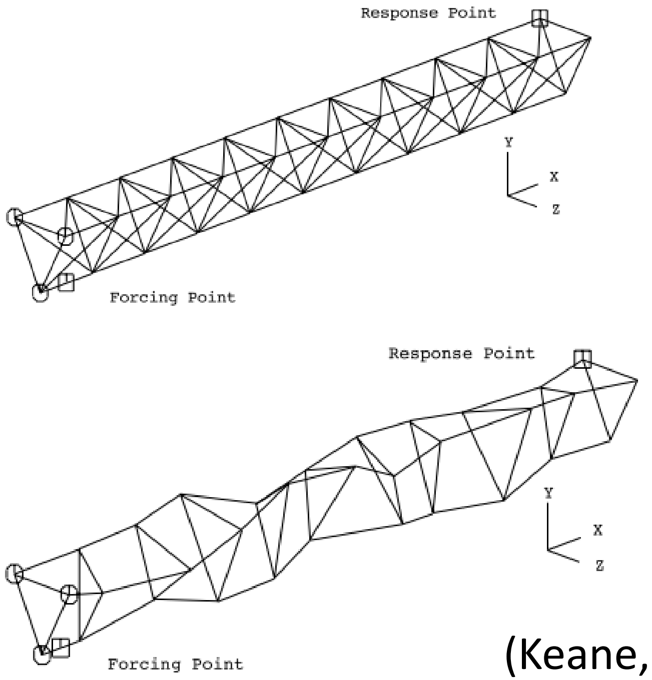


(Koza et al., 2006, p. 11)

Example: Design of a Satellite Boom

- Designed using a genetic algorithm
- 20,000+% improvement in frequency averaged energy levels





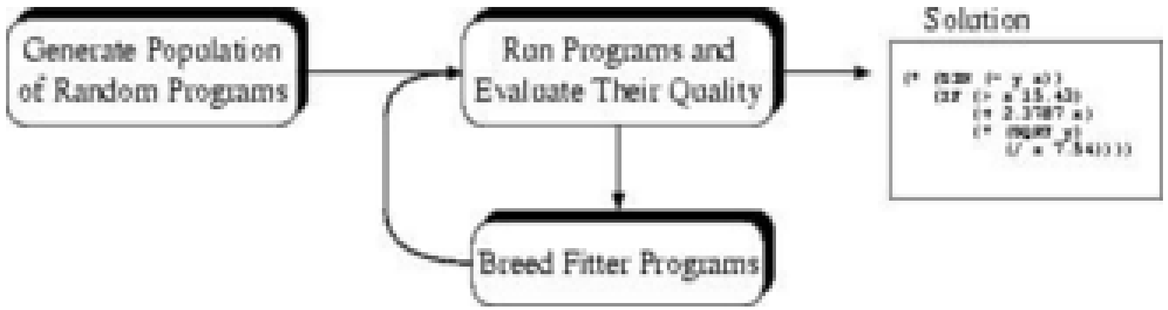
(Keane, 1996)

History

- Visionaries
  - Samuel 1959 – Goal of AI
  - Turing 1948 – Evolutionary search, gene combination, survival of the fittest
- Evolutionary Algorithms , 1962-
  - mutation , populations,
- Genetic Algorithms, 1973-
  - John Holland
  - Crossover
- Genetic Programming, 1989-
  - John Koza
  - Best way to represent a computer program is a computer program

How GP Works

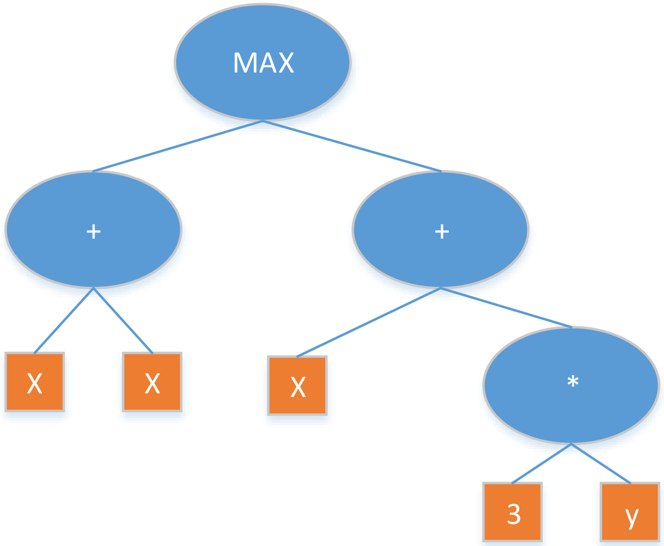
- Preparatory Steps
  - Primitives
  - Fitness Function(s)
- Initialize Population
- Evolve Population
  - Calculate population fitness
  - Select next generation
- Termination Condition



(Poli et al.,2008, p. 2)

GP Representation

- LISP
- (max (+ x x) (+ x (* 3 y)))
- max(x+x,x+3*y)



GP Operations

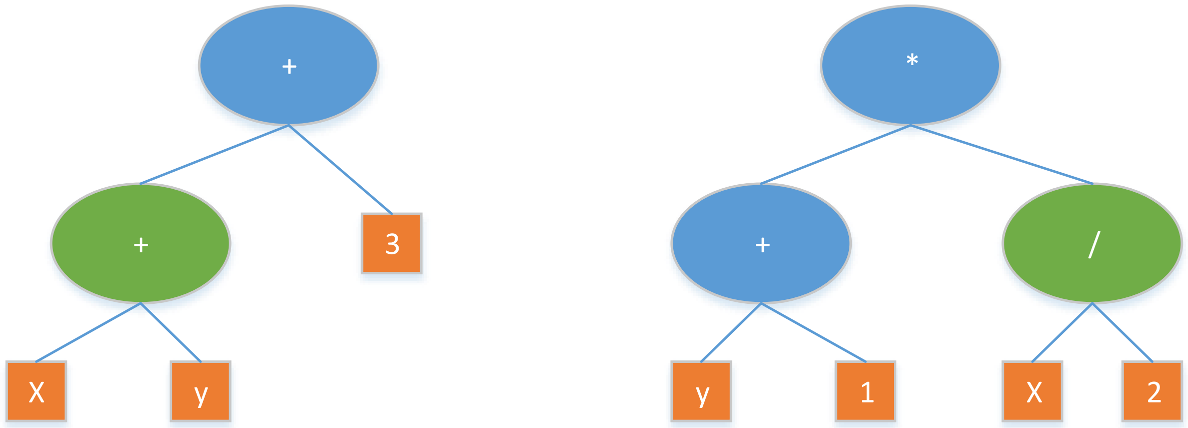
- Probabilistically select an operation
- Crossover
  - Switch two nodes on different individuals
- Mutation
  - Randomly modify an individual (node)
- Reproduction
  - Copy parent, as is, to next generation

GP Selection

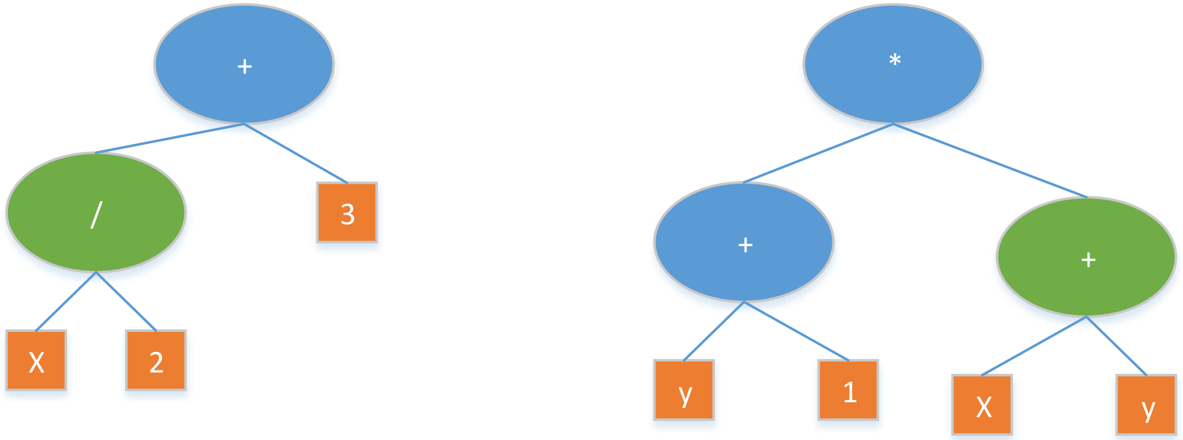
- Need to select one or two individuals for genetic operations
- Selection is probabilistic
- Fitness Proportional Selection
- Tournament Selection

Crossover

Parents

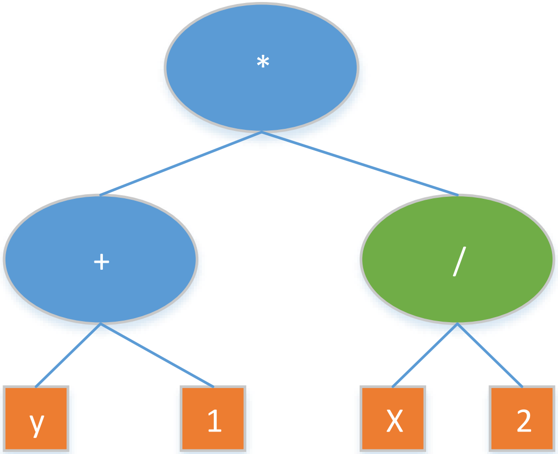


Children

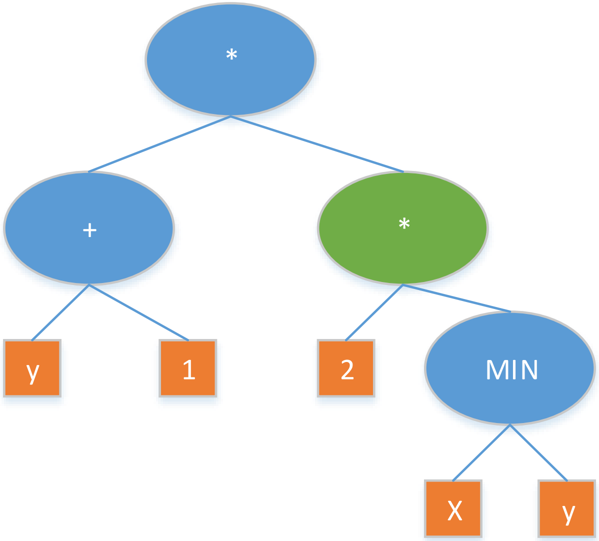


Mutation

Parent

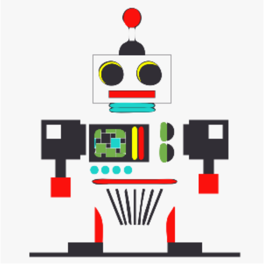


Child

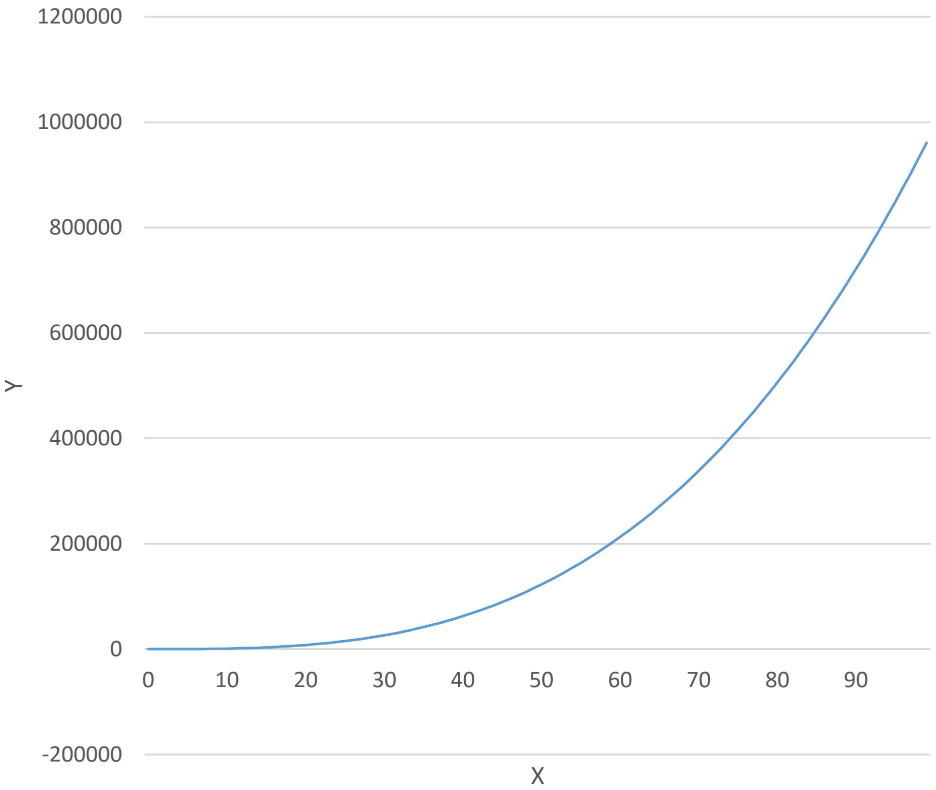


Demo – Symbolic Regression

- Curve Fitting
- $x^3 - x^2 + x - 4$
- Prove that GP works

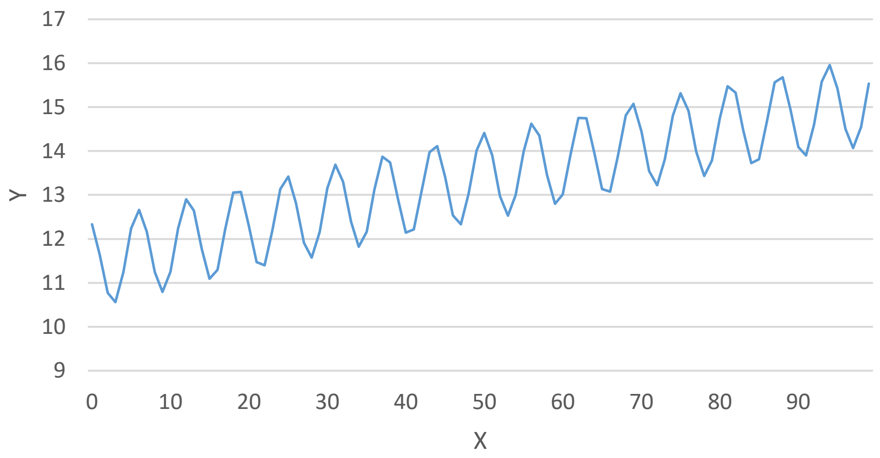


Demo a, b

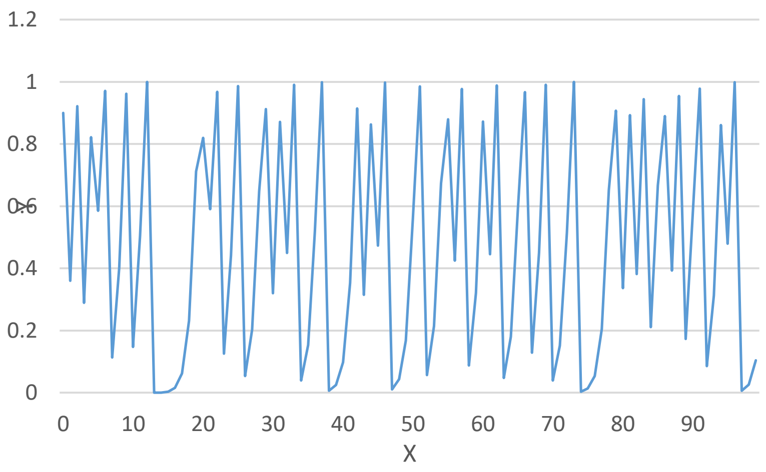


Chaotic Series

- Look random, but are deterministic
- Highly dependent on initial conditions
  - Difficult to predict



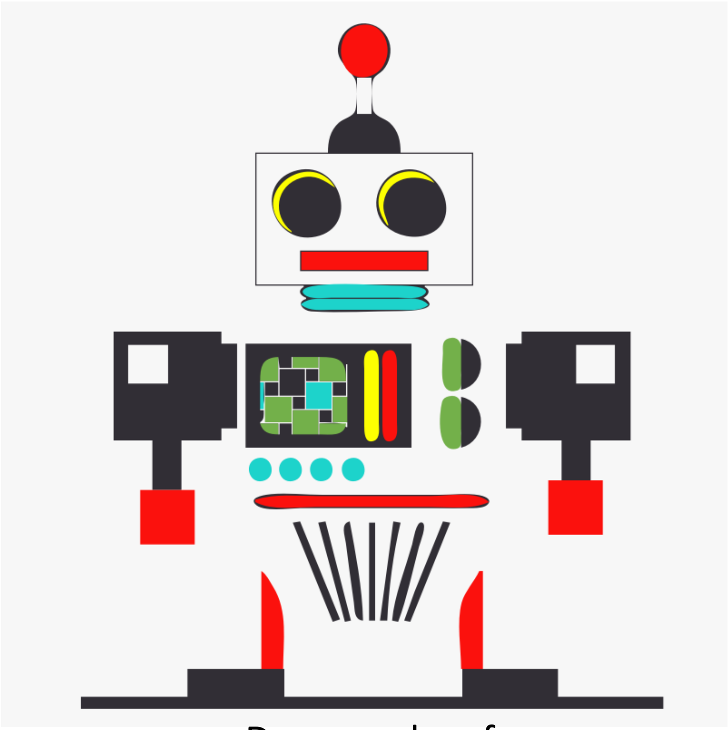
$$Y_t = sin(x - 130) + \sqrt{x + 130}$$



x=0: $Y_{(0)} = 0.9$

X>0: $Y_{(t+1)} = 4Y_t(1 - Y_t)$

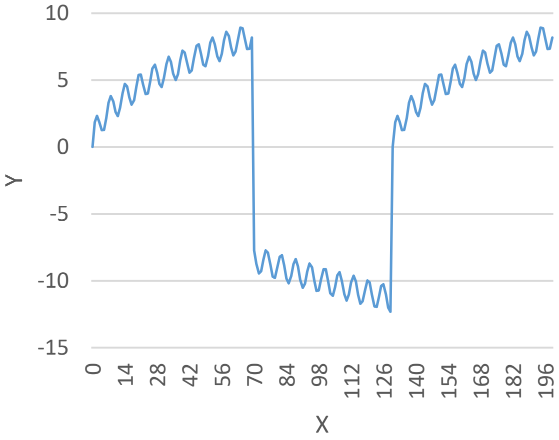
Demo- Chaotic Series Symbolic Regression



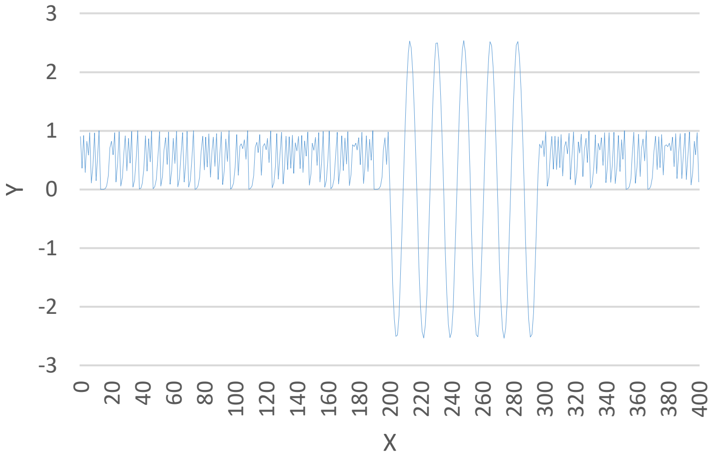
Demo c, d, e, f

Regime Change

- Goal is to uncover underlying data generating process
- This can change over time



0<=x<70: $Y_t = sin(x) + \sqrt{x}$
70<=x<130: $Y_t = cos(x) - \sqrt{x}$
130<=x<200: $Y_t = sin(x - 130) + \sqrt{x - 130}$

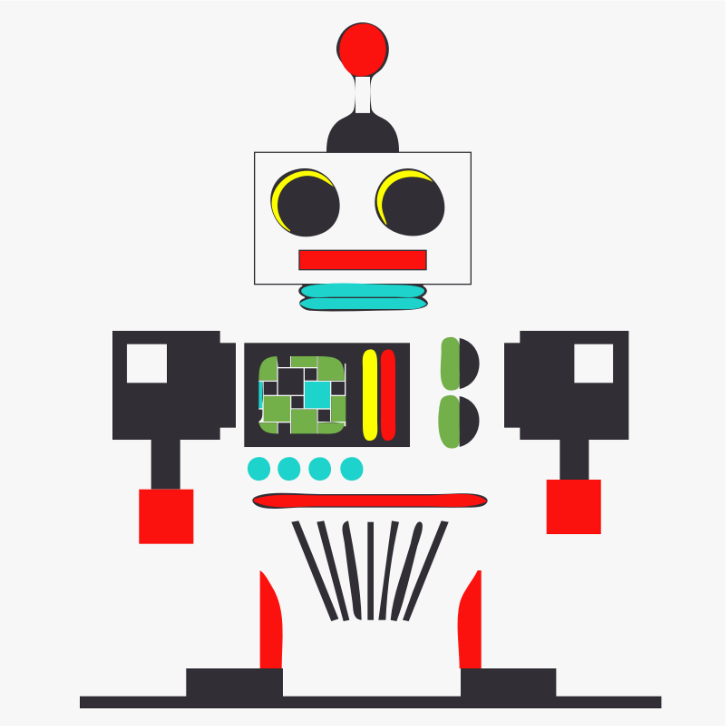


x<200, x>=300: $Y_{(t+1)} = 4Y_t(1 - Y_t)$
200<=x<300: $Y_{(t+1)} = 1.8708Y_t - Y_{t-1}$

S&P 500 index close price during the stock market crash of 2008 (Yahoo, 2013).

$Y_t = f(WTF)$?

Demo- Symbolic Regression Regime Change

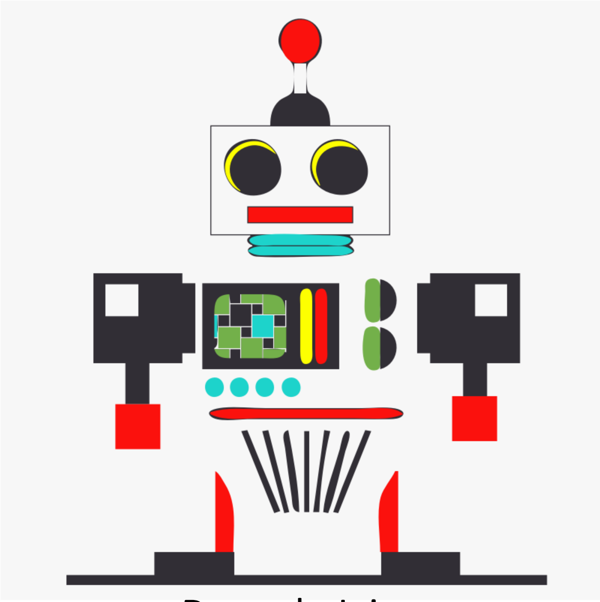


Demo g

Time Series Prediction

- Train on past values
- Predict future values
- Retrain periodically

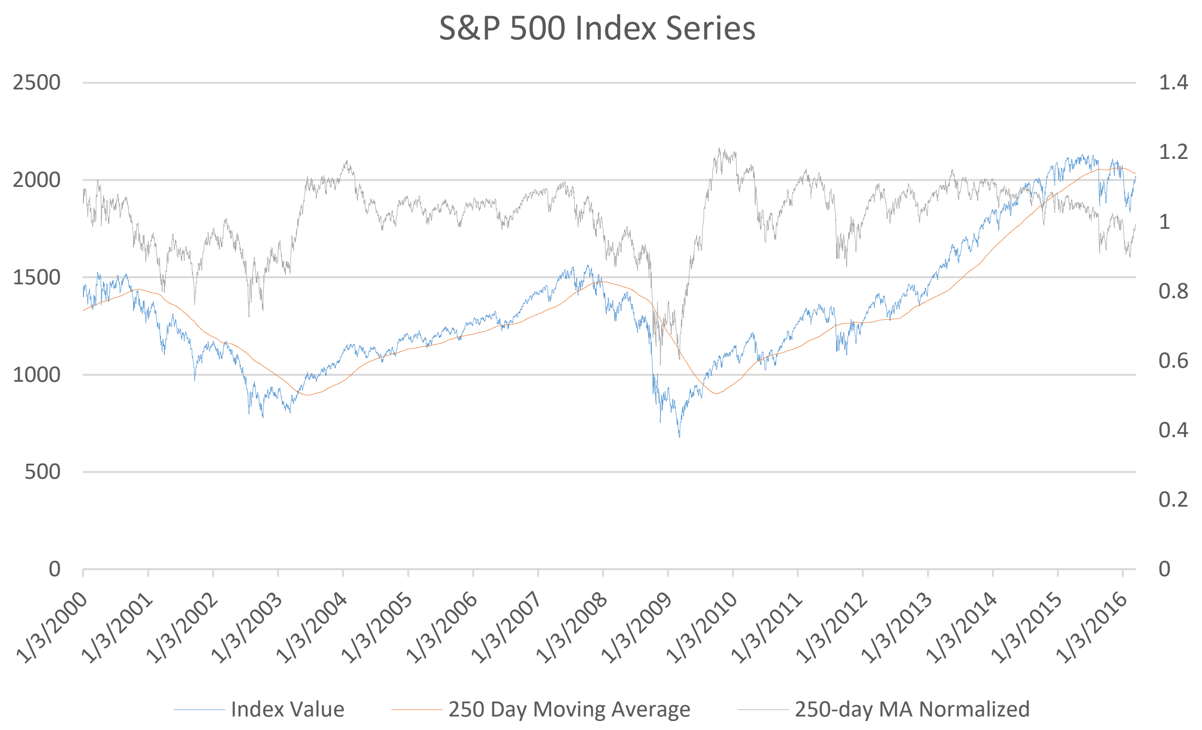
Demo- Chaotic Series Prediction



Demo h, I, j

Market Prediction

- S&P 500 Long-Flat (Invest-don't invest)
- Ignore transaction costs
- Ignore out of market returns
- Predictors
  - S&P 500 Price
  - S&P 500 Volume
  - 250-day MA normalized



GP is a Perfect Match for Market Prediction

- “The interrelationships among the relevant variables is unknown or poorly understood (or where it is suspected that the current understanding may possibly be wrong).”
- “Finding the size and shape of the ultimate solution is a major part of the problem.”
- “Significant amounts of test data are available in computer-readable form.”
- “There are good simulators to test the performance of tentative solutions to a problem, but poor methods to directly obtain good solutions.”
- “Conventional mathematical analysis does not, or cannot, provide analytic solutions”
- “An approximate solution is acceptable (or is the only result that is ever likely to be obtained)”
- “Small improvements in performance are routinely measured (or easily measurable) and highly prized.”

(Poli et al.,2008, pp. 111-113)

Primitive Set

- Hundreds of indicators
  - Ex. (http://www.investopedia.com/active-trading/technical-indicators/)
- Include common technical analysis indicators
  - Momentum- compare to recent average
  - Breakout- compare to recent minimum/maximum
  - Ex. Buy if current price risen by 2% over minimum price last 30 days
- Prefer low level functions
- Better results possible with higher level , packaged indicators?

Primitive set

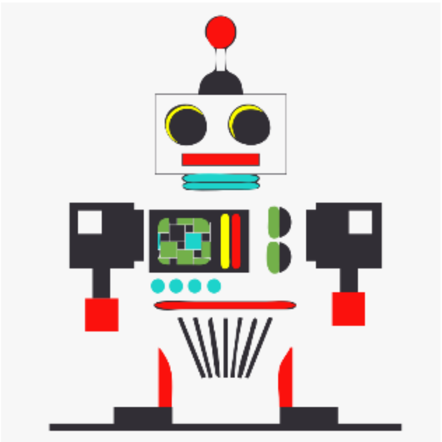
- Functions
  - Add
  - Subtract
  - Multiply
  - Divide
  - Gt
  - Lt
  - And
  - Or
  - Not
  - offsetValue
  - ifElseBoolean
  - movingAverage
  - periodMaximum
  - periodMinimum
  - AbsoluteDifference

- Terminals
  - randomInteger(low high)
  - randomDouble(low high)
  - True
  - False
  - offsetValue(0)

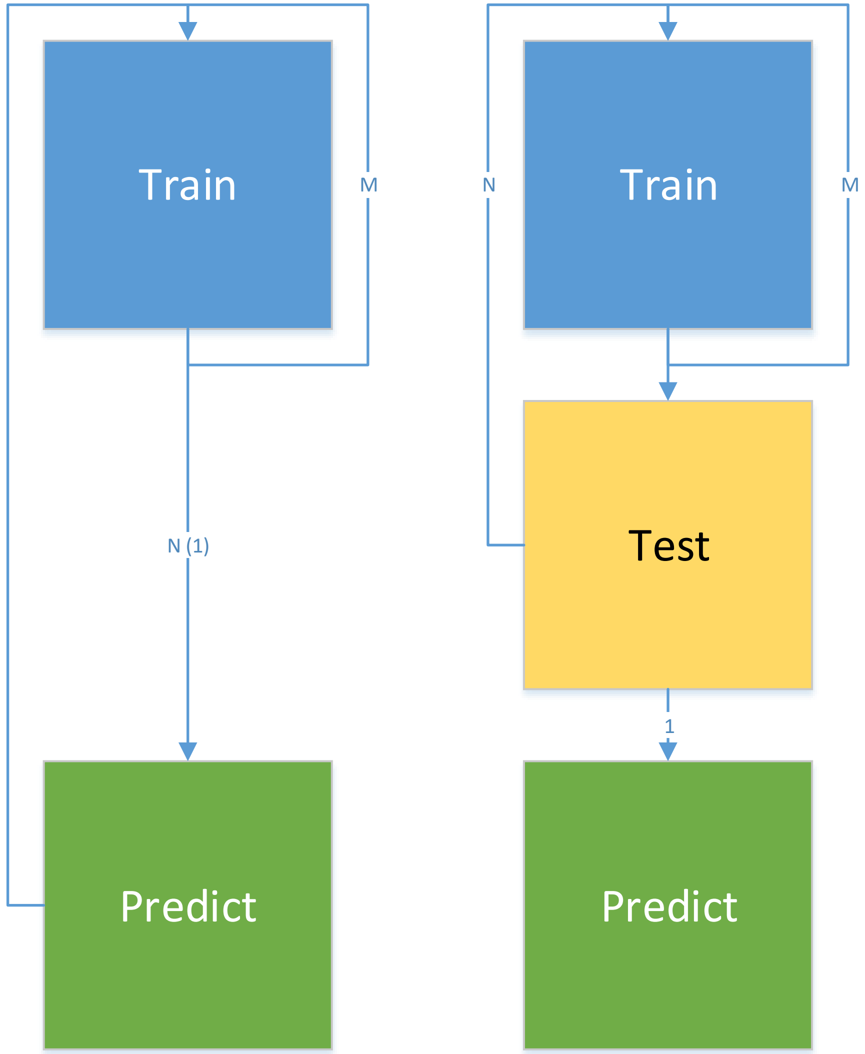
- Hundreds of other technical indicators (http://www.investopedia.com/active-trading/technical-indicators/)

Training Approaches

- Train-Predict-Retrain
- Train-Test-Predict
- Multiple Runs

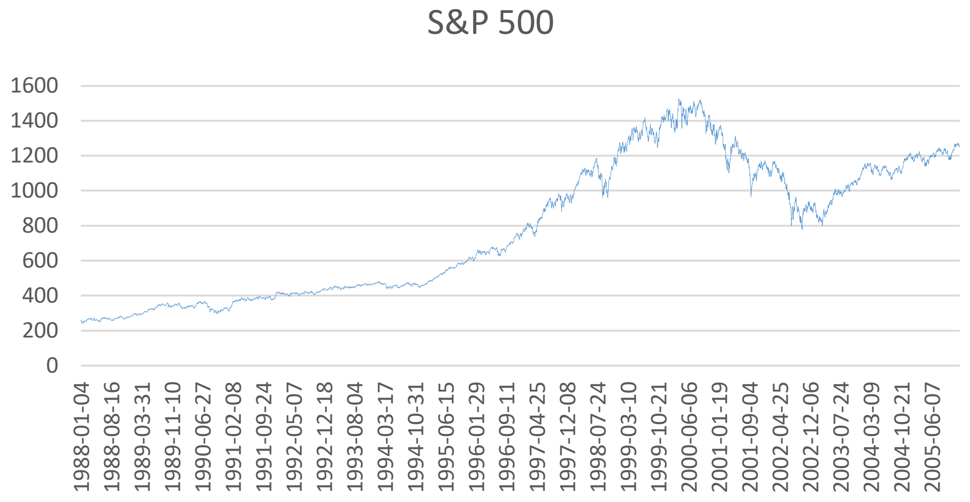


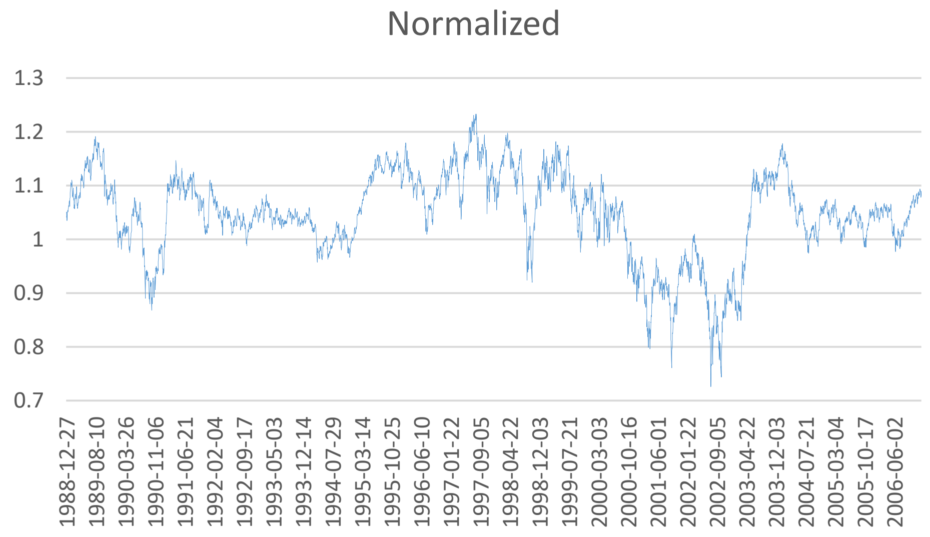
Demo k, l, m



Experiment- Market Prediction

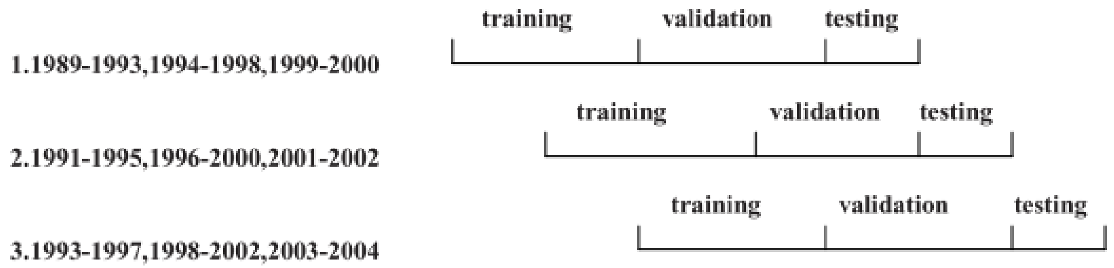
- Investment decisions in S&P 500 Index
- Modeled after (Chen et al., 2008), 1988-2004
- Long-Flat decisions
- Normalized by 250-day moving average
- Fitness = investment gain





Experiment- Market Prediction

- Training-validation-prediction approach (T-V-P)



(Chen et al., 2008, p. 110)

- Training-prediction approach (T-P)
  - Training - 1989-1998
  - Prediction- 1999-2004

Results T-V-P w/Trans Cost

Method	Mean	Std. Dev.	Min	Max	95% CI	# beating benchmark
1999-2000						
Buy & Hold	0.0751					
GP	0.0434	0.0664	-0.1917	0.1197	[0.0250 ... 0.0618]	5/50
ADF	0.0309	0.0798	-0.3054	0.0845	[0.0088 ... 0.0530]	3/50
ADT	0.0510	0.0519	-0.1974	0.1042	[0.0366 ... 0.0654]	5/50
2001-2002						
Buy & Hold	-0.3144					
GP	-0.3693	0.1306	-0.8087	-0.2885	[-0.4055 ... -0.3331]	1/50
ADF	-0.3347	0.0887	-0.7290	-0.1777	[-0.3593 ... -0.3102]	2/50
ADT	-0.3697	0.1390	-0.7450	-0.0134	[-0.4082 ... -0.3312]	1/50
2003-2004						
Buy & Hold	0.3332					
GP	0.2945	0.0497	0.1432	0.3291	[0.2807 ... 0.3083]	0/50
ADF	0.3139	0.0390	0.1170	0.3539	[0.3031 ... 0.3247]	1/50
ADT	0.3247	0.0150	0.2349	0.3522	[0.3205 ... 0.3289]	2/50

(Moskowitz, 2016, p. 119)

Results T-V-P wo/Trans Cost

Method	Mean	Std. Dev.	Min	Max	95% CI	# beating benchmark
1999-2000						
Buy & Hold	0.0751					
GP	0.1494	0.1088	-0.0438	0.4525	[0.1192 ... 0.1795]	35/50
ADF	0.1418	0.1238	-0.0399	0.5112	[0.1075 ... 0.1761]	35/50
ADT	0.1567	0.1099	-0.0068	0.4796	[0.1262 ... 0.1871]	37/50
2001-2002						
Buy & Hold	-0.3144					
GP	-0.3121	0.0573	-0.4081	-0.0348	[-0.3280 ... -0.2962]	17/50
ADF	-0.3023	0.0848	-0.5153	0.0196	[-0.3258 ... -0.2788]	18/50
ADT	-0.2843	0.0635	-0.3924	-0.1245	[-0.3020 ... -0.2667]	32/50
2003-2004						
Buy & Hold	0.3332					
GP	0.3045	0.0929	0.0463	0.5045	[0.2788 ... 0.3303]	15/50
ADF	0.3395	0.1171	-0.0016	0.5597	[0.3070 ... 0.3719]	22/50
ADT	0.3329	0.1202	0.0775	0.6443	[0.2996 ... 0.3663]	29/50

(Moskowitz, 2016, p. 122)

Results T-P w/Trans Cost

Method		Mean	Std. Dev.	Min	Max	95% CI	# beating benchmark
		1999-2000					
Buy & Hold		0.0634					
ADT		0.0018	0.1372	-0.4290	0.2388	[-0.0362 ... 0.1010]	17/50
DyFor GP		-0.0157	0.1101	-0.2690	0.1426	[-0.0463 ... 0.0639]	15/50
		2001-2002					
Buy & Hold		-0.3339					
ADT		-0.1364	0.1014	-0.2964	0.1601	[-0.1645 ... -0.0631]	50/50
DyFor GP		-0.1018	0.0819	-0.2810	0.0817	[-0.1245 ... -0.0426]	50/50
		2003-2004					
Buy & Hold		0.2970					
ADT		0.1035	0.0653	-0.0603	0.2529	[0.0854 ... 0.1507]	0/50
DyFor GP		0.0489	0.0723	-0.1780	0.2156	[0.0289 ... 0.1012]	0/50
		1999-2004					
Buy & Hold		-0.0189					
ADT		-0.0349	0.1933	-0.5395	0.4592	[-0.0884 ... 0.0187]	24/50
DyFor GP		-0.0698	0.1413	-0.3597	0.2136	[-0.1089 ... -0.0306]	15/50

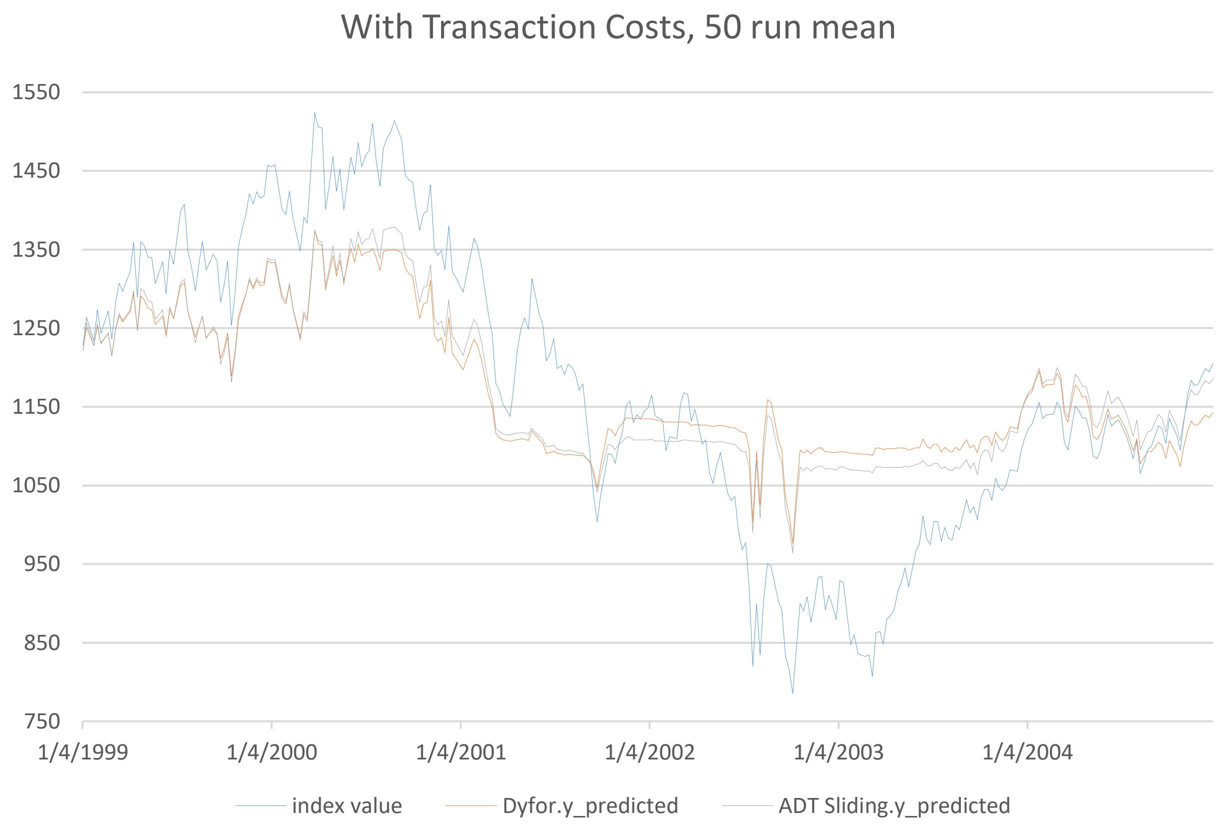
(Moskowitz, 2016, p. 120)

Results T-P wo/Trans Cost

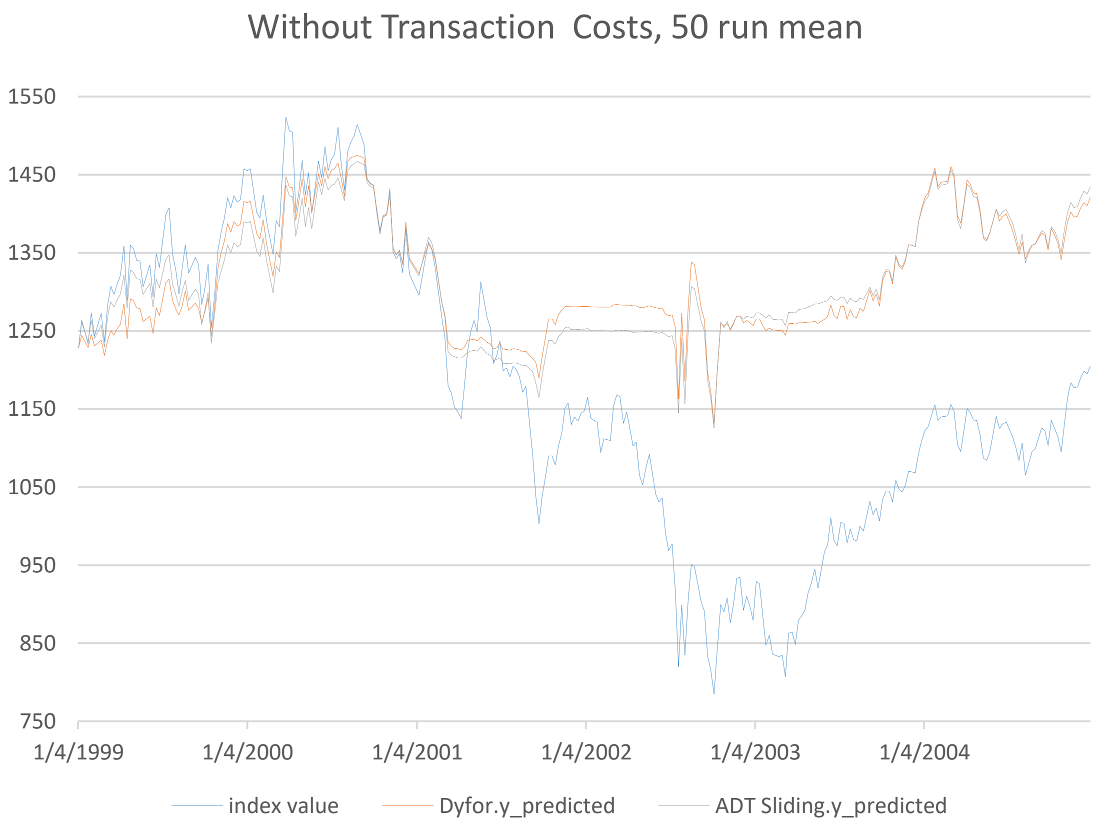
Method	Mean	Std. Dev.	Min	Max	95% CI	# beating benchmark
1999-2000						
Buy & Hold	0.0634					
ADT	0.0788	0.1071	-0.1106	0.3576	[0.0491 ... 0.1562]	27/50
DyFor GP	0.0807	0.1323	-0.1904	0.3408	[0.0440 ... 0.1763]	26/50
2001-2002						
Buy & Hold	-0.3339					
ADT	-0.0524	0.1026	-0.2674	0.1521	[-0.0808 ... 0.0218]	50/50
DyFor GP	-0.0594	0.0862	-0.2314	0.1020	[-0.0833 ... 0.0029]	50/50
2003-2004						
Buy & Hold	0.2970					
ADT	0.1246	0.0782	-0.0132	0.3739	[0.1029 ... 0.1811]	2/50
DyFor GP	0.1233	0.0702	-0.0297	0.2783	[0.1038 ... 0.1740]	0/50
1999-2004						
Buy & Hold	-0.0189					
ADT	0.1683	0.2005	-0.1946	0.6959	[0.1128 ... 0.2239]	39/50
DyFor GP	0.1568	0.1887	-0.2618	0.5762	[0.1045 ... 0.2091]	41/50

(Moskowitz, 2016, p. 124)

ADT vs DyFor GP vs Buy and Hold



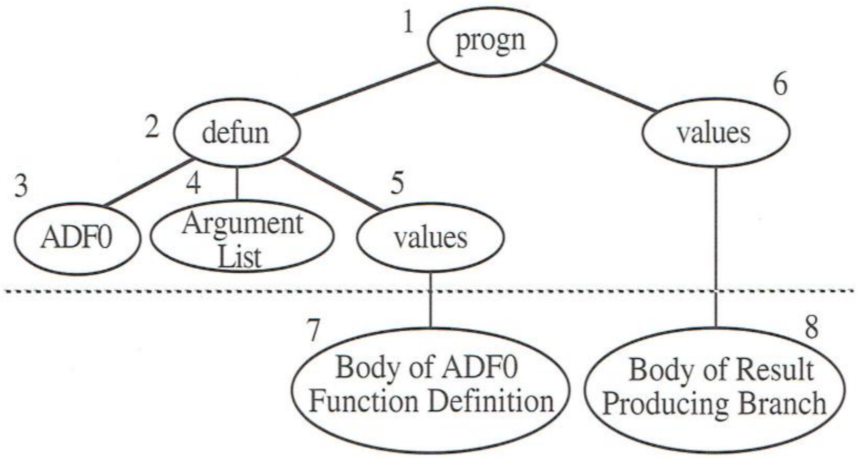
ADT: -0.349%
DyFor GP: -0.698%
B&H: -0.0189%
(Moskowitz, 2016, p. 208)



ADT: +0.1683%
DyFor GP: +0.1568%
B&H: -0.0189%
(Moskowitz, 2016, p. 213)

Advanced GP

- Modularity
  - Automatically Defined Functions
- Strongly-typed GP
  - Closure
- Advanced techniques
  - Looping
  - Memory store
  - Lambdas
  - Recursion
  - Time series regimes (Moskowitz, 2016)
  - Design patterns (Moskowitz, 2016)



(Koza, 1994, p. 74)

Genetic Algorithms

- Non-differentiable / nonlinear optimization problem
- Search for parameters, rules
- Size and shape prescribed
- Bit, Numeric, or other representations
- Ex. Minimize $x^2 - 50y + z^3$, x={0-31},y={0-31},z={0-15}

10011 11000 1011 $19^2 - 50 * 24 + 11^3$=492
00110 11010 1100 $6^2 - 50 * 26 + 12^3$=464

10010 11010 1100 $18^2 - 50 * 26 + 12^3$=752
00111 11000 1011 $7^2 - 50 * 24 + 11^3$=180

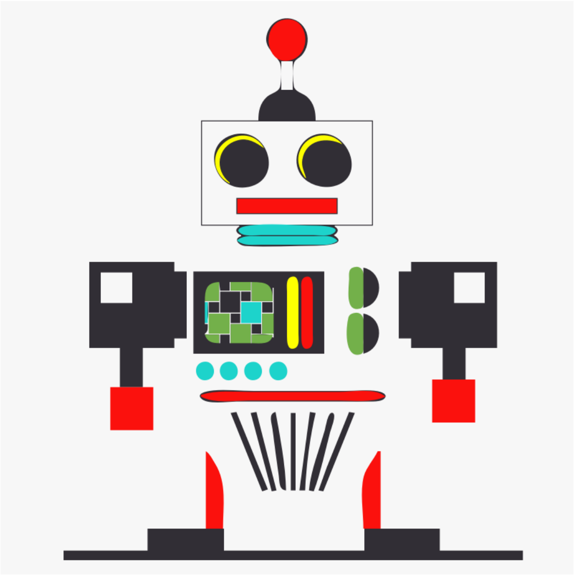
Linear GP

- Sequence of imperative instructions
- Register-based operations
- Machine code, GPU Instructions

(Poli et al.,2008, pp. 61-65)

Demo- Symbolic Regression Regime Change

- Regime determining branch
- Regime specific functions
- Implements template method design pattern



Demo o

Next Steps

- MATLAB (GA only)
- JGAP (Java)
- DEAP (Python)
- Roll your own
- Evolutionary Signals

Not So Shameless Plug

- Evolutionary Signals
  - Develop Buy/Sell signals using genetic programming
  - Minimal financial knowledge and no programming experience required
  - Goals
    - Much larger number of predictor series
    - Crowdsource models
  - Earn revenue from high performing models
  - Open beta testing
  - Visit www.gpsignals.com for more information

Questions?

- Thank you!

- Contact info:

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