Entropy Rate and Profitability of Technical Analysis: Experiments on the NYSE US 100 Stocks

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Outline

- **Entropy Rate :** uncertainty remaining in the next information produced given knowledge of the past ➔ measure of predictability
- Questions :
  - Do stocks exhibit differing entropy rates?
  - Does low entropy imply profitability of TA?
- Methodology :
  - NYSE US 100 Stocks – daily data – 2000-2006
  - TA rules induced using Genetic Programming

Estimating entropy

- Active field of research in neuroscience
- Maximum-likehood ("Plug-in"):
  - construct an n-th order Markov chain
  - not suited to capture long/medium term dependencies
- Compression-based techniques :
  - Lempel-Ziv algorithm, Context-Tree Weighting
  - Fast convergence rate – suited to long/medium term dependencies

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Selected estimator

- Kontoyannis et al 1998

$$\hat{h}_{SM} = \left(\frac{1}{n} \sum_{i=1}^{n} \Lambda_i \right)^{-1} \log_2 n$$

Λ_i : length of the shortest string that does not appear in the *i* previous symbols

Example: $0\ 1\ 1\ 0\ 0\ \underbrace{1\ 0\ 1}\ 1\ 0\ 0$

$$\Lambda_6 = 3$$

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Performance of the estimator

- Experiments :
  - Uniformly distributed r.v. in {1,2,..,8} – theoretical entropy $= -\sum_{i=1}^{8} 1/8 \log_2 p = 3 \ b.p.c.$
  - Boost C++ random generator
  - Sample of size 10000

$$\hat{h}_{SM} = 2.96$$

➢ Note 1 : with sample of size 100000, $\hat{h}_{SM} \geq 2.99$

➢ Note 2 : with standard C *rand()* function and sample size = 10000, $\hat{h}_{SM} = 2.77$

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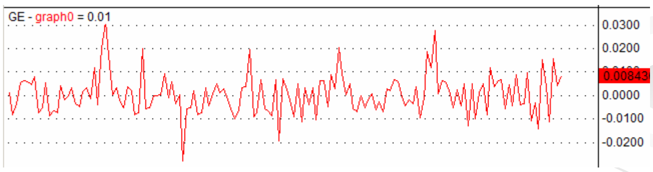
Preprocessing the data (1/2)

- Log ratio between closing prices: $r_t = ln(\frac{p_t}{p_{t-1}})$
- Discretization : $\{r_t\} \in \mathbb{R} \rightarrow \{A_t\} \in \mathbb{N}$



3,4,1,0,2,6,2,...

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Preprocessing the data (2/2)

- Discretization is tricky – 2 problems:
  - How many bins? (size of the alphabet)
  - How many values in each bin?
- Guidelines : maximize entropy with a number of bins in link with the sample size
- Here :
  - alphabet of size 8
  - same number of values in each bin ("homogenous partitioning")

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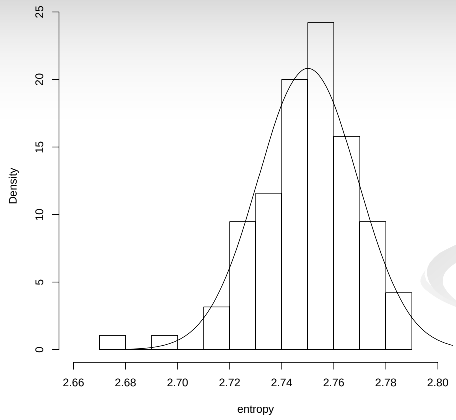
Entropy of NYSE US 100 stocks – period 2000-2006



Mean = Median = 2.75

Max = 2.79

Min = 2.68

Rand() C lib = 2.77 !

Note : a normal distribution of same mean and standard deviation is plotted for comparison.

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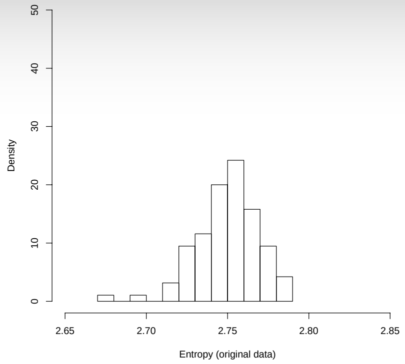
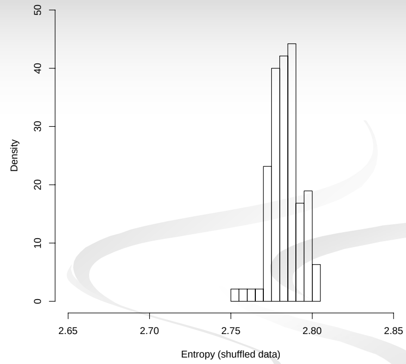
Entropy is high but price time series are not random!



Original time series



Randomly shuffled time series

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Stocks under study

Highest entropy time series

Symbol	Entropy
OXY	2.789
VLO	2.787
MRO	2.785
BAX	2.78
WAG	2.776

Lowest entropy time series

Symbol	Entropy
TWX	2.677
EMC	2.694
C	2.712
JPM	2.716
GE	2.723

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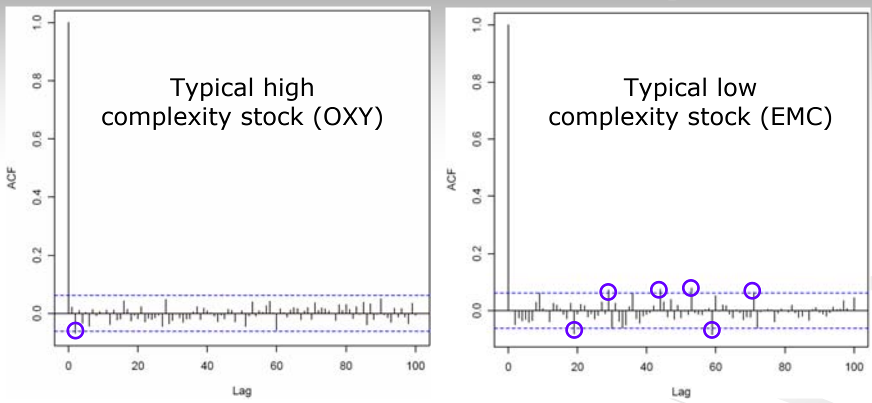
Autocorrelation analysis



➢ Up to a lag 100, there are on average 6 autocorrelations outside the 99% confidence bands for the lowest entropy stocks versus 2 for the highest entropy stocks

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Part 2 : does low entropy imply better profitability of TA?

Addressed here: are GP-induced rules more efficient on low-entropy stocks ?

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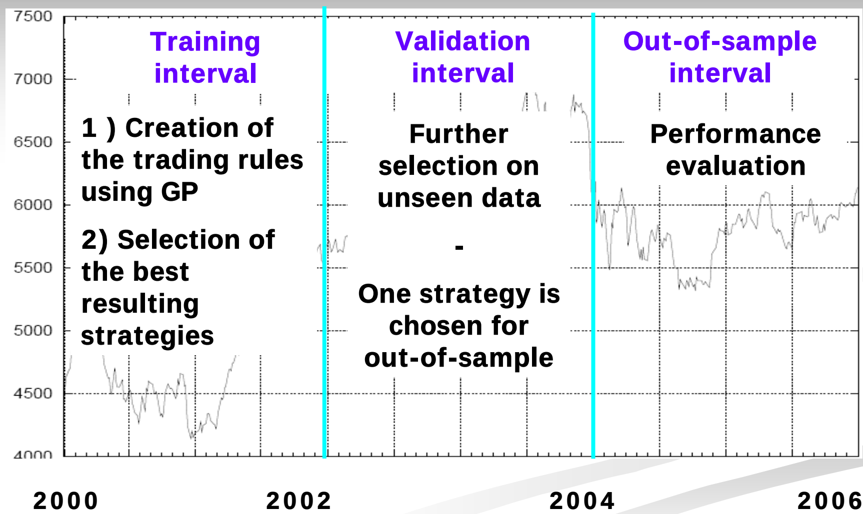
GP : the big picture



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GP performance assessment

- Buy and Hold is not a good benchmark
- GP is compared with lottery trading (LT) of
  - same frequency : avg nb of transactions
  - same intensity : time during which a position is held
- Implementation of LT: random sequences with the right characteristics, e.g:
  0,0,1,1,1,0,0,0,0,0,1,1,1,1,1,1,0,0,1,1,0,1,0,0,0,0,0,0,1,1,1,1,1,1,…
- GP>LT ? LT>GP ? Student’s t-test at 95% confidence level – 20 GP runs / 1000 LT runs

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Experimental setup

- Data preprocessed with 100-days MA
- Trading systems:
  - Entry (long): GP induced rule with a classical set of functions / terminals
  - Exit:
    - Stop loss : 5%
    - Profit target : 10%
    - 90-days stop
- Fitness: net return - Initial equity: 100K$ - position sizing : 100%

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Results: high entropy stocks

	GP net profits	LT net profits	GP>LT?	LT>GP?
OXY	$15.5K\$$	$14K\$$	No	No
VLO	$7K\$$	$11.5K\$$	No	No
MRO	$15K\$$	$18.5K\$$	No	No
BAX	$24K\$$	$13K\$$	**Yes**	No
WAG	$6K\$$	$-0.5K\$$	**Yes**	No

GP is always profitable

LT is never better than GP (at a 95% confidence level)

GP outperforms LT 2 times out of 5 (at a 95% confidence level)

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Results: low entropy stocks

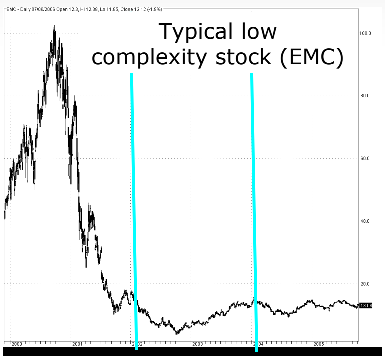
	GP net profits	LT net profits	GP>LT?	LT>GP?
TWX	$-9K\$$	$-1.5K\$$	No	**Yes**
EMC	$-16.5K\$$	$-11K\$$	No	**Yes**
C	$15K\$$	$18.5K\$$	No	No
JPM	$6K\$$	$10K\$$	No	No
GE	$-0.5K\$$	$0.5K\$$	No	No

GP is never better than LT (at a 95% confidence level)

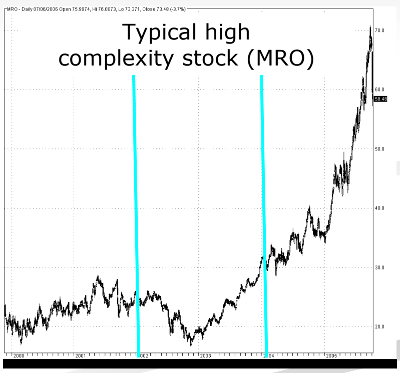
LT outperforms GP 2 times out of 5 (at a 95% confidence level)

Explanations (1/2)

- GP is not good when training period is very different from out-of-sample e.g.



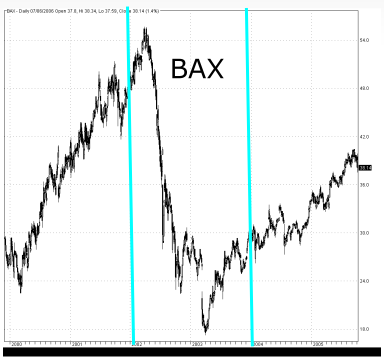
2000 2006

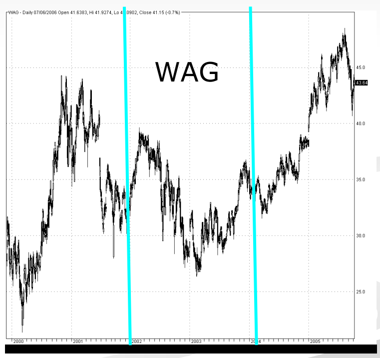


2000 2006

Explanations (2/2)

- The 2 cases where GP outperforms LT : training quite similar to out-of-sample





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Conclusions

- EOD NYSE time series have high but differing entropies
- There are (weak) temporal dependencies
- Here, more predictable ≠ less risks
- GP works well if training is similar to out-of-sample

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Perspectives

- Higher predictability level can be observed at intraday timeframe (what about higher timeframes?)
- Experiments needed with stocks less similar than the ones from NYSE US 100
- Predictability tells us about the existence of temporal patterns – but how easy / difficult to discover them ??

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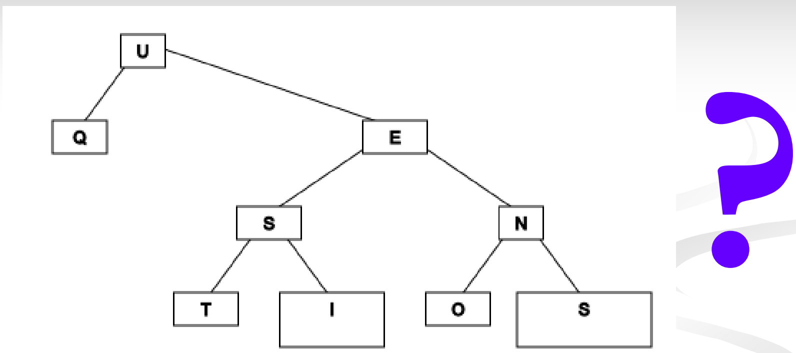

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