A Bottom-up Approach to the Financial Markets

Agent-Based Quantitative Algorithmic Strategies: Ecosystem, Dynamics & Detection

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Thursday 7th March, 2019

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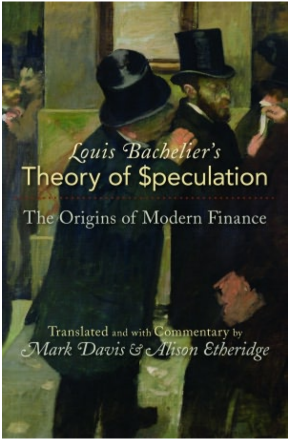
Top-Down (TD): Any **stochastic** quantitative approach which assumes that the **market is random** (or close to random) but for which we can create **interesting dynamic strategies**.



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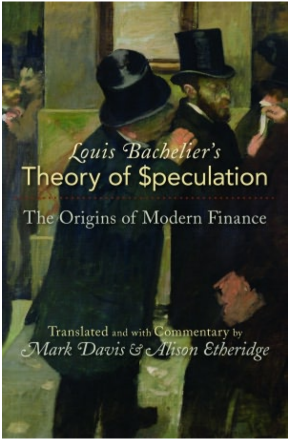

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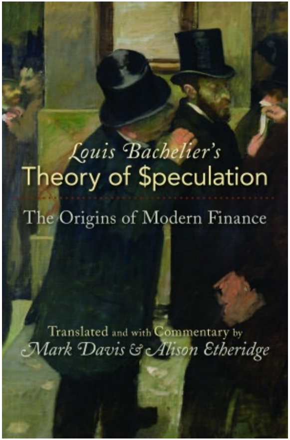

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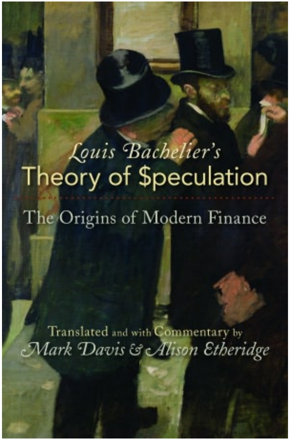

Can we use this new angle to **"solve"** the market?

The Scientific Method for “solving” the market

Question: What do we mean by “solve”?

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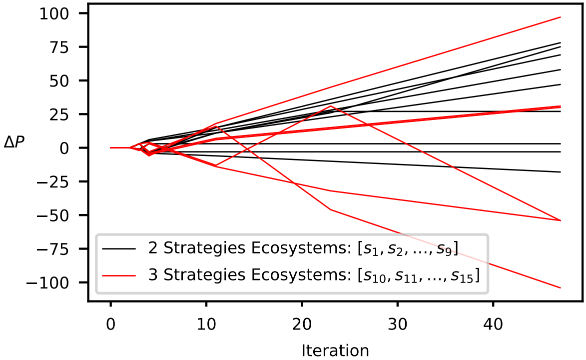

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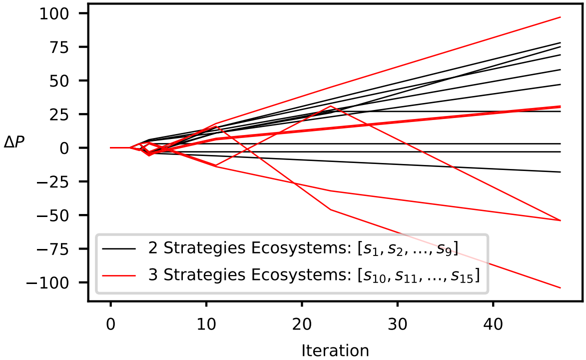

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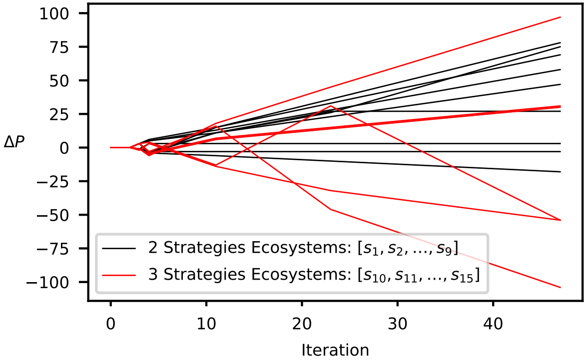
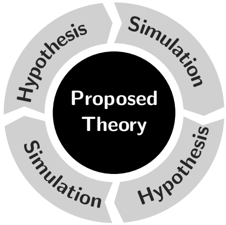


Scientific Method: A good theory can be simulated but simulations can also help bring intuition on what the theory might be [27].



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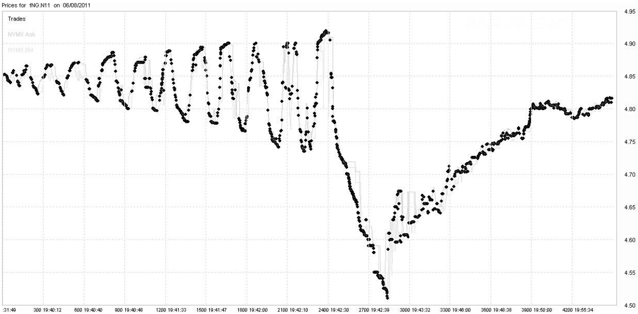

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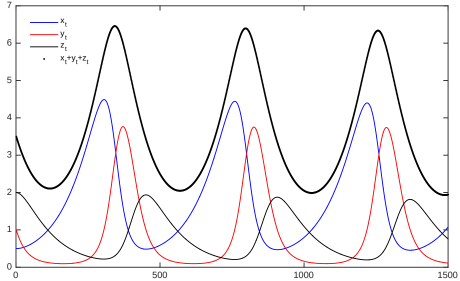
- The **Flash Crashes** (eg: [23]) calls for a **modelling revolution** [5, 11, 6] (**BU vs. TD**): the Brownian motion assumption to model markets is increasingly difficult to defend.

Predator/Prey models

biological ecosystems **predator/prey** (PP) models (a, b, c, d, e, f and g are rate of growth or predation). The relationship between $x(t)$, $y(t)$ and $z(t)$ is **deterministic**:

$$\begin{cases} \frac{dx(t)}{dt} &= ax(t) - bx(t)y(t) \\ \frac{dy(t)}{dt} &= -cy(t) + dx(t)y(t) - ey(t)z(t) \\ \frac{dz(t)}{dt} &= -fz(t) + gy(t)z(t) \end{cases}$$



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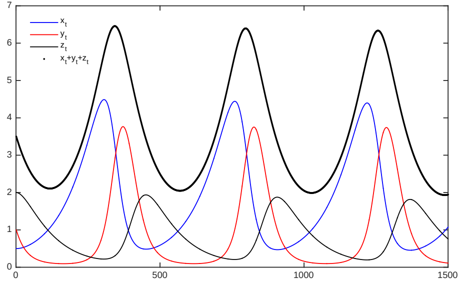

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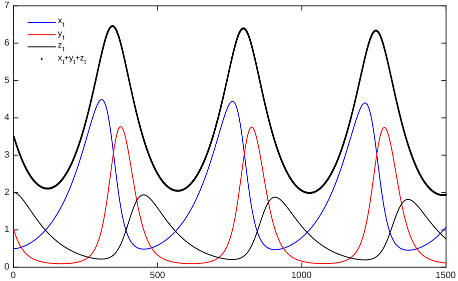
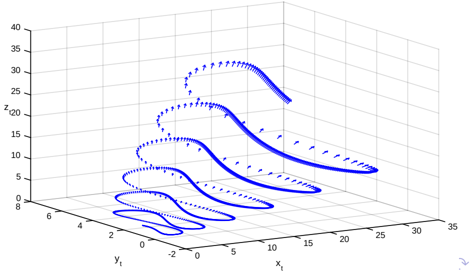
Answering if an **ecosystem** (or by extension financial market) composed of 3 strategies is **stable** would come to studying the Jacobian matrix J. If if all **eigenvalues** of $J(x; y; z)$ have negative real parts then our system is asymptotically **stable**. Though simplistic, the model can easily be expanded to more **complex ecological niches**.

$$J(x; y; z) = \begin{bmatrix} a - by & -xb & 0 \\ yd & -c + dx - ez & -ye \\ 0 & -zg & -f + gy \end{bmatrix}$$





Evolutionary Dynamics

Axelrod's [2, 3] computer tournament and Nowak's work on Evolutionary Dynamics (ED) [24] on invasion need to in uence 21st century Quantitative Finance especially the BU approach.

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The methodology in ED is interesting because the strategies are both systematic & interacting with each other (like it is the case in algo trading).

Generative Adversarial Networks for Electronic Trading

As ML \translation" of ED and PP models, we have Generative Adversarial Networks (GANs) [12], introduced in 2014, usually involve a system of two neural networks competing in a zero-sum game settings. This process continues as long as needed since the lack of data is no longer a problem.

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The communication tool is the order book and the game is not zero-sum game in our research.The strategies are in High Frequency Financial Funnel (HFFF) format [20].

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Architecture Complexity and strategy sophistication explains the incentive for Deep Learning (DL).
Paradoxically we witness potential for regularization as the network becomes more complex.

Genetic Algorithm & NN Complexity

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Question: Can we make an analogy to the predator prey ecosystem? Do we get similar behaviour as the Lotka-Volterra equations [28, 17]?

The Path of Interaction

Answer: not quite but there are few interesting links (exponential grow of the smaller prey/self ful lling strategies such as TF) but they are many issues (classi cation, timescale etc...).

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Strategy	seed'	TF1	TF2	TF1	TF2
Iteration	0		1		2
Signal	N/A	+1	+1	+1	+1
OB	${}_{0}P^{1;1;1;1}$	${}_{0;0}P^{1;1;1}$	${}_{0;0;0}P^{1;1}$	${}_{0;0;0;0}P^{1}$	${}_{0;0;0;0;0}P$
Last Price	100	101	102	103	104
OI	1	1	2	3	4
Price	1	1	1	1	1
P&L	0; 0		1; 0		2; 1

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Sequential Monte Carlo

Sequential Monte Carlo (SMC) methods [9, 10, 16], also know as Particle Filter have emerged as a fashionable tool to track scenarios in the last 15 years [25, 26]. They are the sequential analogue of Markov Chain Monte Carlo (MCMC) methods and similar to importance sampling methods.

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The aims of the PF is to estimate the sequence of hidden parameters (eg: the frequencies of certain types of strategies), based on an indirect observations (eg: the uctuations of the market).

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Each deterministic path corresponds to a sequence of interaction of several strategies for which the sequence and the P&Ls can be traced through our SMC methods by looking at the market price only.

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- We expressed, classic Financial Strategies in HFFF format and shown the incentive for going from from a simple perceptron, to shallow and finally deep learning.
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- Finally we looked at tracking methods using MTT.

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- Increased HFFF complexity does not equate to Invasion : A clear picture did not necessarily emerge from the rst simulations.
- Birth & Death Processes : We need to incorporate a Birth and Death Process to our MTT to make more realistic scenarios.
- Diversity & Stability : In biology diversity in an ecosystem leads to its instability [28, 7] but what about Finance?

Closing Statement with Q&A

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Al-Jarrah, O., Yoo, P., Muhaidat, S., Karagiannidis, G., and Taha, K.
Efficient machine learning for big data: A review.
87–93.

Axelrod, R.
The evolution of cooperation.
Basic Books (1984).

Axelrod, R.
The complexity of cooperation: Agent-based models of competition and collaboration.
Princeton University Press (1997).

Bachelier, L.
Theorie de la speculation.
Annales Scientifiques de lcole Normale Suprieure 3 (17) (1900), 21–86.

Bouchaud, J.-P.
Economics needs a scientific revolution.
Nature 455 (2008), 1181.

Buchanan, M.
Meltdown modelling: Could agent-based computer models prevent another financial crisis?
Nature 460 (2009), 680–682.

Chauvet, E., Paullet, J. E., Previte, J. P., and Walls, Z.
A Lotka-Volterra three-species food chain.
Mathematics Magazine 75 (2002), 243–255.

Cukier, K., and Mayer-Schoenberger, V.
The rise of big data: How it's changing the way we think about the world.
Foreign Affairs 92, 3 (2013), 28–40.

Doucet, A., de Freitas, N., and Gordon, N.
Sequential monte carlo in practice.
New York: Springer-Verlag (2001).

Doucet, A., Godsill, S., and Andrieu, C.
On sequential monte carlo sampling methods for bayesian filtering.
Statistics and Computing 10, 9 (2000), 197–208.

Farmer, J. D., and Foley, D.
The economy needs agent-based modelling.
Nature 460 (2009), 685–686.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y.
Generative adversarial networks.

Johnson, T. C.
Finance and mathematics: Where is the ethical malaise?
The Mathematical Intelligencer 37, 4 (Dec 2015), 8–11.

Lee, J.-G., and Minseo, K.
Geospatial big data: Challenges and opportunities.

Leonard, C.
Apres la crise, lenseignement de la finance repense.

Liu, J., and Chen, R.
Sequential monte carlo methods for dynamic systems.
Journal of the American Statistical Association.

Lotka, A. J.
Elements of physical biology.
Williams & Wilkins Co. (1925).

Mahdavi-Damghani, B.
UTOPE-ia.
Wilmott Magazine 60 (2012), 28–37.

Mahdavi-Damghani, B.
The non-misleading value of inferred correlation: An introduction to the cointelation model.

Wilmott 67 (2013), 50–61.

Mahdavi-Damghani, B.
Introducing the HFTE model: a multi-species predator prey ecosystem for high frequency quantitative financial strategies.
Wilmott Magazine 89 (2017), 52–69.

Mahdavi-Damghani, B., and Roberts, S.
A bottom-up approach to the financial markets agent-based quantitative algorithmic strategies: Ecosystem, dynamics & detection.

Mahdavi-Damghani, B., Welch, D., O'Malley, C., and Knights, S.
The misleading value of measured correlation.
Wilmott 62 (2012), 64–73.

Nanex.
Strange days june 8'th, 2011 - natgas algo, 2011.

Nowak, M.
Evolutionary dynamics : exploring the equations of life.
2006.

Sidenbladh, H.
Multi-target particle filtering for the probability hypothesis density.
Proceedings 6th International Conference on Information Fusion (2003), 800–806.

Sidenbladh, H., and Wirkander, S.
Particle filtering for finite random sets.
IEEE Transactions on Aerospace and Electronic Systems (2003).

Villani, C.
Cedric villani: la simulation numrique est un enjeu majeur pour la societe, 2012.

Volterra, V.
Variazioni e fluttuazioni del numero dindividui in specie animali conviventi.
Mem. Acad. Lincei Roma (1926), 31–113.