**Evolutionary Computational Finance & Economics**

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**What Computational Finance?**

- **What is Artificial Intelligence?**
  - Not easy to define
- **Defined by the activities in the community**
- **Challenging fundamentals in Economics and Finance**
  - Rationality
  - Efficient market

**Why Computational Finance?**

- Forecasting
  - Spotting Opportunities
  - Arbitrage
- Understanding financial markets
  - Bargaining Theory
  - Artificial Markets
  - Evolving Agents

**What are the challenges ahead?**

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**Why Computational Finance?**

<table>
<thead>
<tr>
<th>What can be done now</th>
<th>Enabling technology:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large scale simulation</td>
<td>Must faster machines</td>
</tr>
<tr>
<td>Data warehouse</td>
<td>Much cheaper memory</td>
</tr>
<tr>
<td>Building complex models</td>
<td>Agent-technology</td>
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<tr>
<td>Efficient exploration of models</td>
<td>Evolutionary computation</td>
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<tr>
<td>Decision support</td>
<td>Experimental game theory, constraint satisfaction</td>
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</tbody>
</table>

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**Forecasting**

Is the market predictable?
What exactly is the forecasting problem?

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**Forecasting**

- Will the price go up or down?
  - By how much?
- What prices do we have?
  - Daily? Intraday (high frequency)? Volume?
  - Indices? Economic Models?
- Are Option and Future prices aligned?
  - (i.e. are there arbitrary opportunities?)

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**EDDIE adds value to user input**

- **User inputs indicators**
  - e.g. moving average, volatility, predictions
- **EDDIE makes selectors**
  - e.g. “50 days moving average > 89.76”
- **EDDIE combines selectors into trees**
  - by discovering interactions between selectors
- Finding thresholds (e.g. 89.76) and interactions by human experts is laborious
### An Example Decision Tree

- **Is X's P/E ratio lower than the industry average by >20%?**
  - Yes
  - No

- **Has X's price risen by >5% since a week ago?**
  - Yes
  - No

- **Has X's price fallen by >2% since yesterday?**
  - Yes
  - No

- **Buy**
- **Sell**
- **No Action**

### Syntax of GDTs in EDDIE-2

- **Tree** := "if-then-else" <Condition> <Tree> <Tree> | Decision
- **Condition** := <Condition> "And" <Condition> | <Condition> "Or" <Condition> | "Not" <Condition> |
- **<RelationOperation>** := "=" | "<" | "≤" | "≥" | "" |

- Variable is an indicator / feature
- Decision is an integer, "Positive" or "Negative" implemented
- Threshold is a real number

- **Richer language ⇒ larger search space**

### A taste of user input

<table>
<thead>
<tr>
<th>Given</th>
<th>Expert decision</th>
<th>More input</th>
<th>Define target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily closing</td>
<td>50 days m.a.</td>
<td>Volatility</td>
<td>74% in 21 days?</td>
</tr>
<tr>
<td>90</td>
<td>80</td>
<td>50</td>
<td>1</td>
</tr>
<tr>
<td>99</td>
<td>82</td>
<td>52</td>
<td>0</td>
</tr>
<tr>
<td>87</td>
<td>83</td>
<td>53</td>
<td>1</td>
</tr>
<tr>
<td>82</td>
<td>82</td>
<td>51</td>
<td>1</td>
</tr>
<tr>
<td>……..</td>
<td>……..</td>
<td>……..</td>
<td>……..</td>
</tr>
</tbody>
</table>

### Arbitrage Opportunities

- **Futures are obligations to buy or sell at certain prices**
- **Options are rights to buy at a certain price**
- **If they are not aligned, one can make risk-free profits**
  - Such opportunities should not exist
  - But they do in London

- **Option price: £0.5**
  - Future selling price: £11
  - Option right to buy: £10

### Our EDDIE/FGP Experience

- **Patterns exist**
  - Would they repeat themselves in the future? (EMH debated for decades)
- **EDDIE has found patterns**
  - Not in every series (we don’t need to invest in every index / share)
- **EDDIE extending user’s capability**
  - and give its user an edge over investors of the same caliber

### Automated Bargaining
Automatic Bargaining Overview

- n shared variables
- Cost
- Utility
- Supplier
- Customer
- Supply price defines my cost
- Maximise profit
- Satisfy constraints
  - price
  - purchase
  - sell
  - schedule
- Who do I know?
- Motivation in e-commerce: talk to many

How to bargain?
- Aim: to agree on price, delivery time, etc.
- Constraint: deadlines, capacity, etc.
- Who to serve? Who to talk to next?

Bargaining in Game Theory

- Rubinstein Model:
  - In reality:
    - Offer at time \( t = f(x, y, \tau) \)
    - Is it necessary?
    - Is it rational? (What is rational?)
  - A’s payoff \( x_A \) drops as time goes by
    - A’s Payoff: \( x_A \exp(-\tau, t) \)
  - Important Assumptions:
    - Both players rational
    - Both players know everything
  - Equilibrium solution for A:
    - \( \mu_A = (1 - \delta) / (1 - \delta \mu_A) \)
    - where \( \delta = \exp(-\tau, t) \)

Evolutionary Rubinstein Bargaining, Overview

- Game theorists solved Rubinstein bargaining problem
  - Subgame Perfect Equilibrium (SPE)
- Slight alterations to problem lead to different solutions
  - Outside option
  - Asymmetric information
  - Different time intervals
- Evolutionary computation
  - Succeeded in solving a wide range of problems

Issues Addressed, EC for Bargaining

- Representation
  - Should \( t \) be in the language?
- One or two population?
- How to evaluate fitness
  - Fixed or relative fitness?
- How to contain search space?
- Discourage irrational strategies:
  - Ask for \( x_A > 1 \)?
  - Ask for more over time?
  - Ask for more when \( \delta_A \) is low?

Two populations, co-evolution

- We want to deal with asymmetric games
  - E.g. two players may have different information
- One population for training each player’s strategies
- Co-evolution, using relative fitness
  - Alternative: use absolute fitness

Evolve over time

Representation of Strategies

- A tree represents a mathematical function \( g \)
- Terminal set: \( \{ \delta_A, \delta_B \} \)
- Functional set: \( \{ \tau, \times, \Rightarrow, \} \)
- Given \( g \), player with discount rate \( r \) plays at time \( t \)
  - \( g \times (1 - t) \)
- Language can be enriched:
  - Could have included \( e \) or time \( t \) to terminal set
  - Could have included power \( \tau \) to function set
- Richer language \( \Rightarrow \) larger search space \( \Rightarrow \) harder search problem
Incentive Method: Constrained Fitness Function

- No magic in evolutionary computation
  - Larger search space → less chance to succeed
- Constraints are heuristics to focus a search
  - Focus on space where promising solutions may lie
- Incentives for the following properties in the function returned:
  - The function returns a value in (0, 1)
  - Everything else being equal, lower δ_A → smaller share
  - Everything else being equal, lower δ_B → larger share
  - Note: this is the key to our search effectiveness

Models with known equilibriums

- Complete Information
  - Rubinstein 82 model:
    - Alternative offering, both A and B know δ_A & δ_B
  - Evolved solutions approximates theoretical
- Working on a model with outside option
  - Incomplete Information
    - Rubinstein 85 model:
      - B knows δ_A & δ_B
      - A knows δ_A and δ_{max} & δ_{min} with probability Ω_{max}
    - Evolved solutions approximates theoretical

Models with unknown equilibriums

- Modified Rubinstein 85 models
- Incomplete knowledge
  - B knows δ_B but not δ_A; A knows δ_A but not δ_B
- Asymmetric knowledge
  - B knows δ_A & δ_B; A knows δ_A but not δ_B
- Asymmetric, limited knowledge
  - B knows δ_A & δ_B
  - A knows δ_A and a normal distribution of δ_B
- Working on limited knowledge, outside option and new bargaining procedures

Evolutionary Bargaining, Conclusions

- Demonstrated GP’s flexibility
  - Models with known and unknown solutions
  - Outside option
    - Incomplete, asymmetric and limited information
    - Trying on models with new bargaining procedures
- Co-evolution is an alternative approximation method to find game theoretical solutions
  - Relatively quick for approximate solutions
  - Relatively easy to modify for new models
- Genetic Programming with incentive / constraints
  - Constraints used to focus the search in promising spaces

Agent-based Artificial Market

- Built to understand market behaviour better

Santa Fe Institute:
- Exogenous returns (set by experimenter)
- (Evolutionary) Classifier Systems

LeBaron:
- Endogenous returns
- Does market exhibit empirical features (“Stylized facts”)?
- Effects of the traders’ memory

Agent-based Artificial Market

![Diagram of an agent-based artificial market with agents interacting to form a market]

- Farmers: Trend following agents + (Fundamental) value investors

Artificial Market

Markets are efficient in the long run
How does the market become efficient?
Do all agents converge in their opinions?
Wind-tunnel testing for new markets

Herd behaviour?
More on markets analysis

- Arifovic:
  - Endogenous foreign exchange markets
  - Used GA to evolve decision rules that determine the agents’ portfolios

- Kirman:
  - Complex dynamics generated from simple behaviour inspired by ants
  - Agent-based model to studied fish market in Marseille

*And many more interesting works observed / reported*

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Evolving Agents

Evolving Agents

- Should agents adapt to the environment?
- Co-evolution

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The Red Queen Thesis

*In this place it takes all the running you can do, to keep in the same place.*

- Chen & Yeh:
  - Endogenous prices
  - Agents are GPs
  - “Peer pressure” (relative wealth) lead to agents retraining themselves
  - Retraining is done by “visiting the business school”

- Markose, Martinez & Tsang:
  - CCFAE work in progress
  - Wealth exhibits Power Law
  - Wealth drives retraining
  - Retraining is done by EDDIE

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Evolving Agents

- Sanders, Cliff:
  - Zero intelligence agents
  - Market efficiency can be obtained by zero-intelligence agents as long as the market rules are properly set.
  - This result challenges the neoclassical models regarding the utility maximization behaviour of economic agents

- Schulenburg & Ross
  - Heterogenous agents (agents may have different knowledge)
  - Agents modelled by classifier systems
  - Exogenous prices
  - Beat buy-and-hold, trend follower and random walk agents

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Wind-tunnel tests for new markets

- New markets are being invented
- Building evolvable agents helps to test new market mechanism
  - Tesfatsion & Koesrindartoto’s design of California’s electricity market: Agent-based testing is cost effective
  - Essex: modelling credit card payment market
    - Evolving agents for tuning bank strategies;
    - Can be used for tuning government regulations

Conclusions

Evolutionary Computational Finance & Economics

- Computing has changed the landscape of finance and economics research
  - We can do what couldn’t in the past
- Evolutionary computation plays a major role
  - Forecasting investment opportunities
  - Approximating subgame equilibrium in bargaining
  - Understanding markets
  - Wind-tunnel testing new market mechanism

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