Computational Finance & Economics
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IEEE Technical Committee on Computational Finance and Economics

What Computational Finance?
- What is Artificial Intelligence?  
  - Not easy to define
- Defined by the activities in the community

Why Computational Finance?
- Challenging fundamentals in Economics and Finance  
  - Rationality
  - Efficient market

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

EDDIE adds value to user input
- User inputs indicators  
  - e.g. moving average, volatility, predications
- 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

Syntax of GDTs in EDDIE-2

A taste of user input

Our EDDIE/FGP Experience

Arbitrage Opportunities

Portfolio Optimization
Portfolio Optimization

- Typically:
  - High risk → high return
  - Diversification reduces risk

- Task: find a portfolio
  - Maximize return, minimize risk

- Difficulty: constraints, e.g.
  - No more than n stocks
  - Not too much on one stock
  - Not too much on one sector

- Optimization problem:
  - Note: how to measure risk?

Automated Bargaining

Bargaining in Game Theory

- Rubinstein Model:
  - In reality:
    - Offer at time t = f(tA, tB, t)
  - Is it necessary?
  - Is it rational? (What is rational?)
  - A's payoff xA drops as time goes by:
    - A's Payoff = xA exp(-c,tA)
  - Important Assumptions:
    - Both players rational
    - Both players know everything
  - Equilibrium solution for A:
    - \( \mu_A = (1 - \delta_B)/(1 - \delta_B) \)
    - where \( \delta_B = \exp(-c, A) \)
  - Optimal offer: \( x_A = \mu_A \) at t=0
  - Notice: No time t here

Evolutionary Rubinstein Bargaining, Overview

- Game theorists solved Rubinstein bargaining problem
  - Subgame Perfect Equilibrium (SPE)
- Slight alterations to problem lead to different solutions
  - asymmetric, incomplete information
  - Outside option
- Evolutionary computation
  - Succeeded in solving a wide range of problems
  - EC has found SPE in Rubinstein's problem
  - Can EC find solutions close to Nash SPE?
- Co-evolution is an alternative approximation method to find game theoretical solutions
  - Less time for approximate SPEs
  - Less modifications for new problems

Issues Addressed in EC for Bargaining

- Representation
  - Should 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 xA = ?
  - Ask for more over time?
  - Ask for more when \( \delta_B \) is low?
Representation of Strategies

- A tree represents a mathematical function $g$
- Terminal set: $\{1, \delta_A, \delta_B\}$
- Functional set: $\{+, \times, \delta, +\}$
- Given $g$, player with discount rate $r$ plays at time $t$ $g \times (1 - r)^t$
- Language can be enriched:
  - Could have included $e$ or time $t$ to terminal set
  - Could have included power $^*$ 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 $\rightarrow$ 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 $\delta_A$ $\rightarrow$ smaller share
  - Everything else being equal, lower $\delta_B$ $\rightarrow$ 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 $\delta_A$ or $\delta_B$
  - Evolved solutions approximates theoretical
  - Working on a model with outside option
- Incomplete Information
  - Rubinstein 85 model:
    - B knows $\delta_A$ or $\delta_B$
    - A knows $\delta_A$ and $\delta_B$, $\delta_A^{\text{max}}$ and $\delta_B^{\text{min}}$ with probability $\Omega_{\text{min}}$
  - Evolved solutions approximates theoretical

Models with unknown equilibriums

- Modified Rubinstein 85 models
- Incomplete knowledge
  - B knows $\delta_B$ but not $\delta_A$; A knows $\delta_A$ but not $\delta_B$
- Asymmetric knowledge
  - B knows $\delta_A$ and $\delta_B$; A knows $\delta_A$ but not $\delta_B$
- Asymmetric, limited knowledge
  - B knows $\delta_A$ and $\delta_B$; A knows $\delta_A$ and a normal distribution of $\delta_B$
- Working on limited knowledge, outside option
- Future work: new bargaining procedures

Evolutionary Bargaining, Conclusions

- Demonstrated GP’s flexibility
  - Models with known and unknown solutions
  - Outside option
  - Incomplete, asymmetric and limited information
- 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
Artificial Market

Markets are efficient in the long run
- How does the market become efficient?
- Wind-tunnel testing for new markets

Evolving Agents

Should agents adapt to the environment?
- Co-evolution

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 QPs
  - “Peer pressure” (relative wealth) lead to agents retraining themselves
  - Retraining is done by “visiting the business school”
- Markose, Martinez & Tsang:
  - CC Federation work in progress
  - Wealth exhibits Power Law
  - Wealth drives retraining
  - Retraining is done by EDDIE

Evolving Agents

- Schulenburg & Ross
  - Heterogenous 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
  - Exogenous prices
  - Beat buy-and-hold, trend follower and random walk agents

Conclusions

Computational Finance & Economics

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

Questions & Comments?

Edward Tsang
http://www.cfeslab.net
http://cswww.essex.ac.uk/CSP/finance
http://cswww.essex.ac.uk/CSP/edward
- Nobel Economic Prize 2001
- Senior VP and Chief Economist, World Bank, 1997-2000
- Critical view on globalization
- Founder, The Initiative for Policy Dialogue, to:
  - Explore policy alternatives
  - Enable wider civic participation in economic policymaking

Opportunities and Challenges in CF&E
- Wide varieties of financial applications
- Different types of learning mechanism
- Different markets to simulate
- Wind-tunnel tests will become the norm
  - Yet to be developed
- Challenges:
  - Large number of parameters to tune
  - What can the simulations tell us?

The Computational Finance Community
- Conferences:
  - IEEE International Conference on Computational Intelligence for Financial Engineering
  - Annual Workshop on Economics with Heterogeneous Interacting Agents (WEIRA 2003 at Leeds, Mackay, Stanford, Dempsey)
  - International Conference on Computing in Economics and Finance
  - International Joint Conference on Autonomous Agents and Multi-Agent Systems
- Useful websites:
  - Tesfatsion’s Agent-based Computational Economics
  - Chen’s AI-FINCON Research Centre
  - IEEE Network on Computational Finance and Economics
  - IEEE Technical Committee on Computational Finance and Economics

Rationality
Rationality is the assumption behind many economic theories
What does being rational mean?
Are we rational?
The CIDER Theory
What is Rationality?

- Are we all logical?
- What if \textit{Computation} is involved?
- Does \textit{Consequential Closure} hold?
  - If we know P is true and P $\rightarrow$ Q, then we know Q is true
  - We know all the rules in Chess, but not the optimal moves
- “Rationality” depends on computation power!
  - Think faster $\Rightarrow$ “more rational”

CIDER: Computational Intelligence Determines Effective Rationality (1)

- You have a product to sell.
- One customer offers £10
- Another offers £20
- Who should you sell to?
- Obvious choice for a rational seller

CIDER: Computational Intelligence Determines Effective Rationality (2)

- You are offered two choices:
  - to pay £100 now, or
  - to pay £10 per month for 12 months
- Given cost of capital, and basic mathematical training
- Not a difficult choice

CIDER: Computational Intelligence Determines Effective Rationality (3)

- Task:
  - You need to visit 50 customers.
  - You want to minimize travelling cost.
  - Customers have different time availability.
- In what order should you visit them?
- This is a very hard problem
- Some could make wiser decisions than others

“Bounded Rationality”

- Herbert Simon:
  - Most people are only partly rational, and are in fact emotional/irrational in part of their actions
  - “Boundedly” rational agents behave in a manner that is nearly as optimal with respect to its goals as its resources will allow
  - Resources include processing power, algorithm and time available
- Quantifiable definition needed?

Efficient Market Hypothesis

- Financial assets (e.g. shares) pricing:
  - All available information is fully reflected in current prices
- If EMH holds, forecasting is impossible
  - Random walk hypothesis
- Assumptions:
  - Efficient markets (one can buy/sell quickly)
  - Perfect information flow
  - Rational traders
**Does the EMH Hold?**

- It holds for the long term
- "Fat Tail" observation:
  - Big changes today often followed by big changes (either + or −) tomorrow
- How fast can one adjust asset prices given a new piece of information?
  - Faster machines certainly help
  - So should faster algorithms (CIDER)

**Test: Syntax – GDTs in EDDIE-2**

- Tree: “if-then-else” Condition | Decision
- Condition: “And” | Condition | Condition
- "Or" | Condition
- "Not" | Condition
- Variable <RelationOperation> Threshold
- <RelationOperation> ::= "<" | "=" | ">

Variable is an indicator feature
Decision is an integer, “Positive” or “Negative” implemented
Threshold is a real number

- Richer language ⇒ larger search space

**Centre for Computational Finance and Economic Agents 2005-06**

- Economics
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  - Abhinay Muthoo
- Computer Science
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- Administrators:
  - Lynda Triolo
  - Julie Peirson
- Students:
  - 30 PhD + Master
- City Associates
  - HSBC, Barclays, Old Mutual, etc.

**Evolutionary Computation: Model-based Generate & Test**

- A Model could be a population of solutions, or a probability model
- A Candidate Solution could be a vector of variables, or a tree
- The Fitness of a solution is application-dependent, e.g., drug testing
- Generate: select, create/mutate vectors / trees
- Test

**GP Operators**

- Mutation: change a branch

**Agent-based Artificial Market**

- Better understand the market
  - What makes a market efficient?
  - Ask "what happen if...?"

- Strategy Design
- Wind Tunnel Market Testing
  - Designing new markets
- Agent 1
- Agent 2
- Agent n
- Artificial Market

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**Wind-tunnel tests for new markets**

- New markets are being invented
  - Bay, electricity, roads
- Model new markets to check if they work
  - Answer what-if questions
  - Evolve agents to approximate equilibriums

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**Red Queen**

... Now, here, you see, it takes all the running you can do, to keep in the same place. If you want to get somewhere else, you must run at least twice as fast as that! ...

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**The Collaborator Problem**

*Manager*

*Engineers*

*Jocks*

*Controllers*

*Regions*

*Agent-based Payment Card Market Model*

**Government:** public interest drives regulations

- Consistent policy observed with static actors
- Decision, decisions, interactions at the point of sale
- Costumer's fees and benefits

**Possible Objectives:**
- Maximize profit
- Maximize market share
- Learning optimal strategies
- Merchant's fees and benefits

**Research Agenda:**
To define for management a mechanism to achieve all-win solutions

**Agents:**

- Connected topology