What Computational Finance?

- Apply advanced computing to finance & economics
  - No consensus on definition
- Defined by activities
  - Computational intelligence
  - Optimization
- Challenging fundamentals in Economics and Finance
  - Rationality
  - Efficient market
  - Homogeneous traders
- Forecasting and Trading
  - (Rare) opportunities, Arbitrage
- Algorithmic Trading
- Optimization
  - Portfolio optimization
- Modelling, Simulation & Machine Learning
  - Automated Bargaining
  - Artificial Markets for
    - Evolving strategies
    - Wind-tunnel testing

Why Computational Finance? What are the challenges ahead?

Why Computational Finance?

What can be done now:	Enabling technology:
Large scale simulation	Must faster machines
Data warehouse	Much cheaper memory
Building complex models	Agent-technology
Efficient exploration of models	Evolutionary computation (Multi-Obj) Optimisation
Decision support	experimental game theory, constraint satisfaction

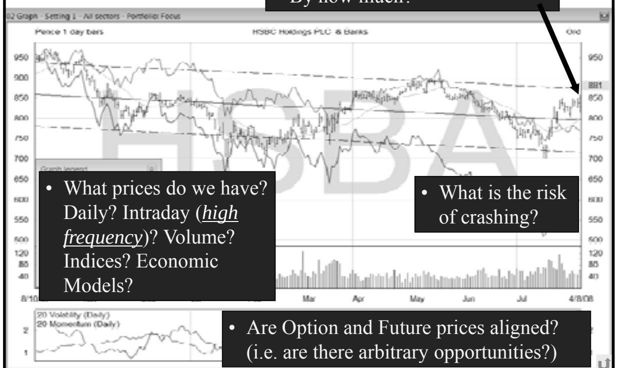
James Butler Jin Li Alma Garcia Tsang

Forecasting

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

Forecasting

- Will the price go up or down? By how much?

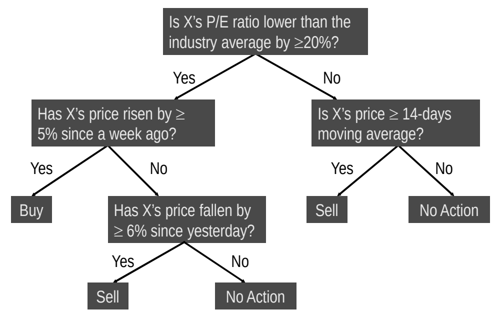


- What prices do we have? Daily? Intraday (*high frequency*)? Volume? Indices? Economic Models?
- What is the risk of crashing?
- Are Option and Future prices aligned? (i.e. are there arbitrary opportunities?)

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

<Tree> ::= "If-then-else" <Condition> <Tree> <Tree> | Decision
<Condition> ::= <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

A taste of user input

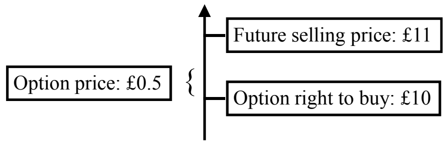
Given	Expert adds:	More input:		Define target:
Daily closing	50 days m.a.	Volat-ility	…..	↑4% in 21 days?
90	80	50		1
99	82	52		0
87	83	53		1
82	82	51		1
…..	…..	…..		…..

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

Arbitrage Opportunities

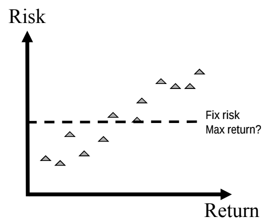
- Futures are obligations to buy or sell at certain prices
- Options are rights to buy at a certain price
- If they are not aligned, one can make risk-free profits
  - Such opportunities should not exist
  - But they do in London



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?



AlgorithmicTrading

What is AlgorithmicTrading?

- Program makes decisions autonomously
  - Could be expert system, machine learning, technical trading

Computer vs Human Traders

- Programs work *day and night*, humans can't
- Programs react in *miliseconds*, humans can't
- Programs can be *fully audited*, humans can't
- When programs make mistakes, one can *learn* and *change* the culprit codes
  - Failed human traders simply change jobs
- Expertise in computer programs *accumulates*
  - Human traders leave with his/her experience

>> Not to mention costs, emotion, hidden agenda, etc.

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FAQ in Automated Trading

- ***Is the market predictable?***
  - It doesn't have to be: just code your own expertise
  - Market is not efficient anyway, herding has patterns
- ***How can you predict exceptional events?***
  - No, we can't
  - Neither can human traders
- ***How can you be sure that your program works?***
  - No, we can't
  - Neither were we sure about Nick Leeson at Barrings
  - Codes are more auditable than humans
  - If you can improve your odds from 50-50 to 60-40 in your favour, you should be happy

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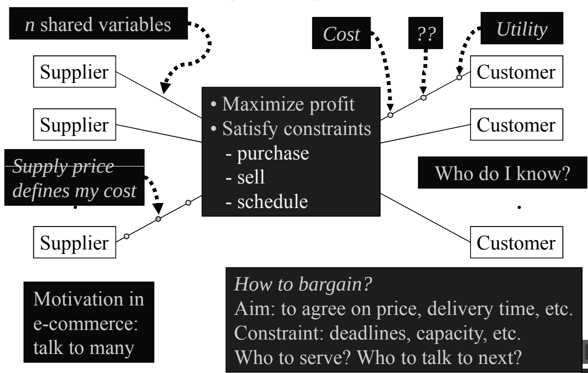
Automated Bargaining

Automatic Bargaining Overview



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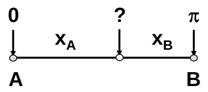
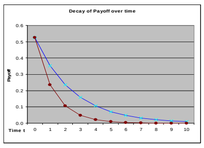
Bargaining in Game Theory

- Rubinstein Model:

In reality:
Offer at time $t = f(r_A, r_B, t)$
Is it necessary?
Is it rational? (What *is* rational?)





- A's payoff x_A drops as time goes by
  A's Payoff = $x_A \exp(-r_A t\Delta)$
- Important Assumptions:
  - Both players rational
  - Both players know *everything*
- Equilibrium solution for A:
  $\mu_A = (1 - \delta_B) / (1 - \delta_A\delta_B)$
  where $\delta_i = \exp(-r_i \Delta)$

Optimal offer:
$x_A = \mu_A$
at t=0

Notice:
No time *t* here

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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 unknown SPE?
- Co-evolution is an *alternative approximation* method to find game theoretical solutions
  - Less time for approximate SPEs
  - Less modifications needed for new problems

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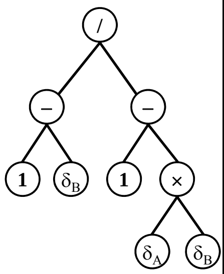
Issues Addressed in EC for Bargaining

- 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 δ_A is low?



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Representation of Strategies

- A tree represents a mathematical function g
- Terminal set: $\{1, \delta_A, \delta_B\}$
- Functional set: $\{+, -, \times, \div\}$
- 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 → larger search space → harder search problem

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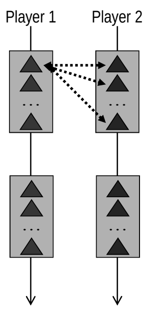
Two populations – co-evolution

- 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



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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 certain properties in 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

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Models with known equilibriums

Complete Information
- Rubinstein 82 model:
  - Alternative offering, both A and B know δ_A & δ_B
- Evolved solutions approximates theoretical
- Evolved solutions for problems with outside option

Incomplete Information
- Rubinstein 85 model:
  - B knows δ_A & δ_B
  - A knows δ_A and δ_B^{weak} & δ_B^{strong} with probability Ω_{weak}
- Evolved solutions approximates theoretical

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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
- Also worked on limited knowledge, outside option
- Future work: new bargaining procedures

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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

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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

Agent-based Artificial Markets

	Agents	Markets
Applications	• How to design strategies? – Given model of market – Evolving robust strategies	• Market mechanism design – Enabling scientific testing – Regulatory design
Fundamental	• Equilibrium strategies? – What would they be? – What if agents change?	• Market efficiency – How does it come about? – Under what assumptions?

Rich and challenging research, EC plays vital part

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

Evolving Agents

- Sunders, 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

Modelling Simulation and Machine Learning

Hani Hagras
Fuzzy Systems for Modelling and reasoning

Edward Tsang
Computational finance
Constraint satisfaction
Machine Learning

Qingfu Zhang
Mathematical modelling
Optimisation
Machine Learning

Research Agenda in Modelling

- Modelling involves
  - Identifying stake holders, and
  - Describing their relations
- Relations are described
  - Mathematically, or
  - Procedurally
- Modelling give us a chance to find equilibrium of the system

Research Agenda in Simulation

- Given a model, equilibrium can be found mathematically in simple models
- In complex models, <u>simulation</u> is the only practical way to find equilibrium
- Simulation may reveal conditions which lead to undesirable outcomes
  - Such as a crash in the stock market
  - One may introduce policies to remove such conditions

Machine Learning in modelling

- Suppose you want to find a trading strategy
- You may build a model and simulate the performance of your strategy
- Then you may change your strategy and try again
- How many models can you test by hand?
- <u>Machine learning</u> does the search for you (day and night)

Sample Projects in Modelling

- Software Wind-tunnels project
  - Vernon Smith (Economics Nobel Prize laureate, 2002) wind-tunnel tested new auction designs
  - A number of projects have been developed in CCFEA
- High frequency finance project (Olsen sponsored)
  - Model trader behaviour in order to understand the market.
- Automated bargaining project
  - Approximated equilibrium through reinforcement learning
- Flexible workforce management project (BT sponsored)
  - Study different ways to allocate jobs to technicians.
- Related project: constraint satisfaction and optimization
  - Computational techniques used in some of the above projects

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Why Modelling?

- Modelling has been used extensively, e.g.
  - War plans, wind-tunnels for aeroplane & car design
- A cost-effective way to assess a situation.
- Stress testing: answering "*what-if*" questions
- Machine learning enables us to *learn* policies and business strategies.
- Modelling enables us to scientifically evaluate such policies and strategies.

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Remarks on Modelling

- Could we be wrong?
  - Of course we will make mistakes!
- "*All models are wrong, but some are useful*" (George Box 1987).
- But a model allows us to improve scientifically
  - Whereas "*intuition*" goes when people depart
- "*More calculation is better than less, Some calculation is better than none*" (translation, The Art of War by Sun Zi 6BC).

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Modelling, Simulation and Machine Learning

For more information:

http://www.bracil.net/info/modelling

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
- Our vision: bottom-up micro behaviour analysis

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Questions & Comments?

Edward Tsang
http://www.bracil.net/finance
http://edward.bracil.net/
(or just search for Edward Tsang)

Supplementary Information

Joseph Stiglitz

- 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

Game Theory Hall of Frame

1994 Nobel Prize

John Harsanyi

John Nash

Reinhard Selten

2005 Nobel Prize

Robert Aumann

Thomas Schelling

Future of Computational Finance

Opportunities and Challenges in CF&E

- Opportunities
  - New dimensions in market understanding (info)
  - Computer trading will become the norm
  - Wind-tunnel tests will become the norm
- Challenges:
  - Different types of learning mechanism
  - Large number of parameters to tune
  - What can the simulations tell us?

The Computational Finance Community

- Conferences:
  - IEEE International Conference on Computational Ineelligence for Financial Engineering
  - Annual Workshop on Economics with Heterogenous Interacting Agents (WEHIA 2005 at Essex, Markose, Sunders, Dempster)
  - International Conference on Computing in Economics and Finance
  - International Joint Conference on Autonomous Agents and Multi-Agent Systems
- Useful web sites:
  - Tesfatsion's Agent-based Computational Economics
  - Chen's AI-ECON Research Centre
- IEEE Network on Computational Finance and Economic
- 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 ***Computation*** is involved?
- Does ***Consequential Closure*** hold?
  - If we know P is true and P → 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 → "more rational"

"Bounded Rationality" / CIDER Theory

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

The CIDER Theory

- Rationality involves Computation
- Computation has limits
- Herbert Simon: Bounded Rationality
- Rubinstein: model bounded rationality by explicitly specifying decision making procedures
- Decision procedures involves algorithms + heuristics
- Computational intelligence determines effective rationality
- Where do decision procedures come from?
  - Designed? Evolved?

1978 Nobel Economic Prize Winner

- Artificial intelligence
- "For his pioneering research into the decision-making process within economic organizations"
- "*The social sciences, I thought, needed the same kind of rigor and the same mathematical underpinnings that had made the "hard" sciences so brilliantly successful.* "
- Bounded Rationality
  - *A Behavioral model of Rational Choice* 1957

Herbert Simon (CMU)

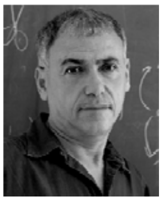
Artificial intelligence

Sources: http://nobelprize.org/economics/laureates/1978/ http://nobelprize.org/economics/laureates/1978/simon-autobio.html

"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?

Modelling Bounded Rationality (1998)



Ariel Rubinstein
New York University

- Rational decisions are optimal decisions
  - But decisions makers often try to satisfy constraints
  - Rather than finding optimality
- Rationality comes from decision making procedures
  - Procedures should be specified explicitly
  - This put the study of procedures on the research agenda

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

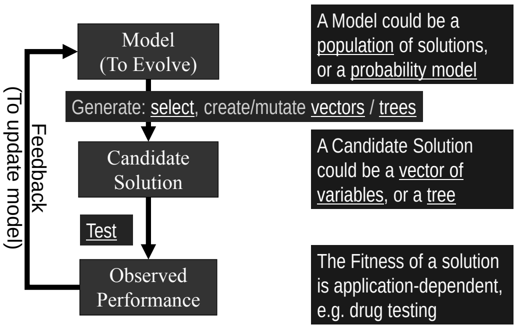
Does the EMH Hold?

- 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)

Evolutionary Computation

A very brief introduction
Genetic Programming

Evolutionary Computation: Model-based Generate & Test



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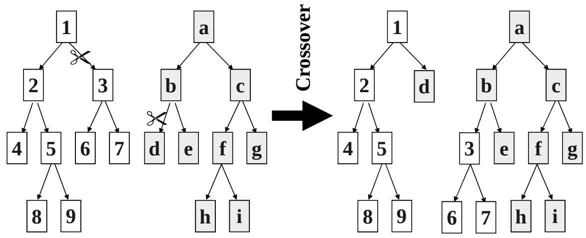
GP Operators



Mutation: change a branch

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Wind-tunnel Testing

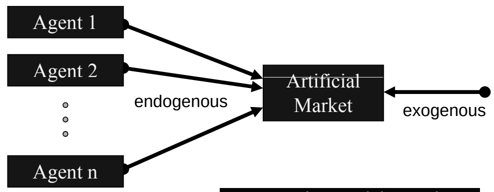
Understanding the market
Searching for market mechanism
Learning strategies

Agent-based Artificial Market

Application

Strategy Design
- How to do well in market

Wind Tunnel Market Testing
- Designing new markets



Fundamental

What happens when agents evolve?

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

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Wind-tunnel tests for new markets

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

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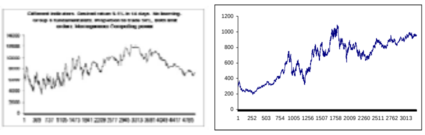
Artificial Markets

Understanding the Stock Market

CHASM Research Summary



Ref: AI-ECON, Giardina et al 2003, other markets

Questions:
→How does the price change?
→What is the effect of learning by traders?

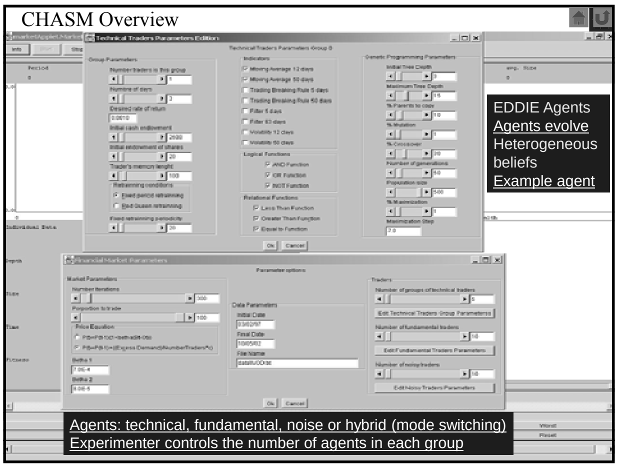
CHASM Platform

EDDIE
Fundamental
Noise
Artificial Market

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! …

CHASM Overview



EDDIE Agents
Agents evolve
Heterogeneous beliefs
Example agent

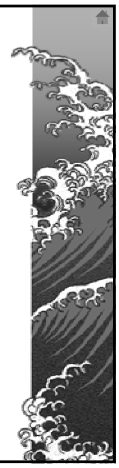
Agents: technical, fundamental, noise or hybrid (mode switching)
Experimenter controls the number of agents in each group

Artificial Finance Market Conclusions

- Platform supports wide range of experiments
- Conditions for stylized facts identified in endogenous, realistic market
- Agents must be competent and realistic
  - Some must observe fundamental values
- *Learning* agents (EDDIE-based):
  - Statistical properties of returns and wealth distribution changed
  - No need for fundamental trader!

Credit Card Payment Market

An Agent-based approach



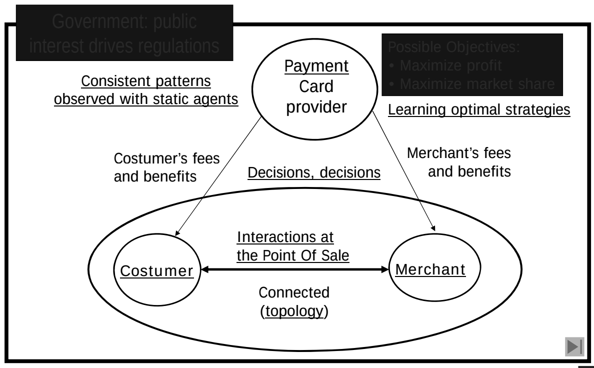
Why Modelling?

- Scientific Approach
  - Modelling allows scientific studies.
  - Human expert opinions are valuable,
  - But best supported by scientific evidences
- Multiple Expertise
  - models can be built by multiple experts at the same time
  - The resulting model will have the expertise that no single expertise can have.
- Models are investments
  - Models will never leave the institute as experts do.
  - Investments can be accumulated.

Why Agent Modelling

- Agent modelling allows
  - Heterogeneity
  - Geographical distribution
  - Micro-behaviour to be modelled
- Representative models don't allow these
- Micro-behaviour makes the market

Agent-based Payment Card Market Model



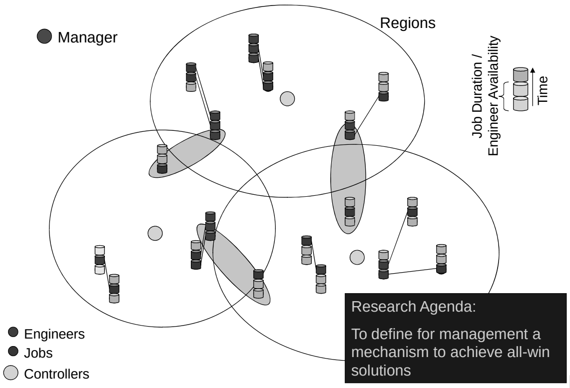
Conclusion, Credit Card Payment Analysis

- Market behavior is complex and hard to analyze
- APCM is useful for studying the card market
  - It is a good model of consumers and merchants behavior
  - Could be used to predict demands
- GPBIL could be used for searching strategies under certain requirements
- Observation: rich results… e.g.
  - Market info determines outcomes
  - More information → less dominance

Market-based Scheduling

Staff Empowerment
for BT's workforce scheduling

The Collaborator Problem



Agent-based Payment Card Market Model