AI, FinTech and Big Data

- Landscape and Applications

Longbing Cao

The Data Science Lab
University of Technology Sydney, Australia

www.datasciences.org

Agenda

- A brief review of classic to modern AI research in finance
  - The area of AI in finance
  - Pros and cons of AI techniques in finance
- Some examples on modelling cross-market couplings
  - Learning cross-market couplings for pool manipulation detection and financial crisis analysis
  - Vine copula + deep neural networks for asymmetric cross-market dependency modelling and portfolio investment

A Brief Review of AI in Finance

Several relevant activities on AI in finance

- IJCAI2020 Special Track on AI in FinTech
- IJCAI2020 panel on AI in FinTech
- IEEE Intelligent Systems: Special Issue on AI and FinTech
- DSAA'2020: Journal Track on Data Science and AI in FinTech
- ACM conference on AI in finance

https://datasciences.org/fintech/:

- AI in Finance: A Review, http://dx.doi.org/10.2139/ssrn.3647625, 2020
- AI in finance: Challenges and opportunities
- AI in FinTech: A Research Agenda, https://arxiv.org/abs/2007.12681, 2020
- Data Science Thinking: The Next Scientific, Technological and Economic Revolution, Springer, 2018
- Data Science: Profession and Education. IEEE Intelligent Systems, 2019
- Data Science: A Comprehensive Overview. ACM Computing Surveys, 2017
- Data Science: Challenges and Directions. Communications of the ACM, 2017
- Data Science: Nature and Pitfalls. IEEE Intelligent Systems, 2016

The search trend

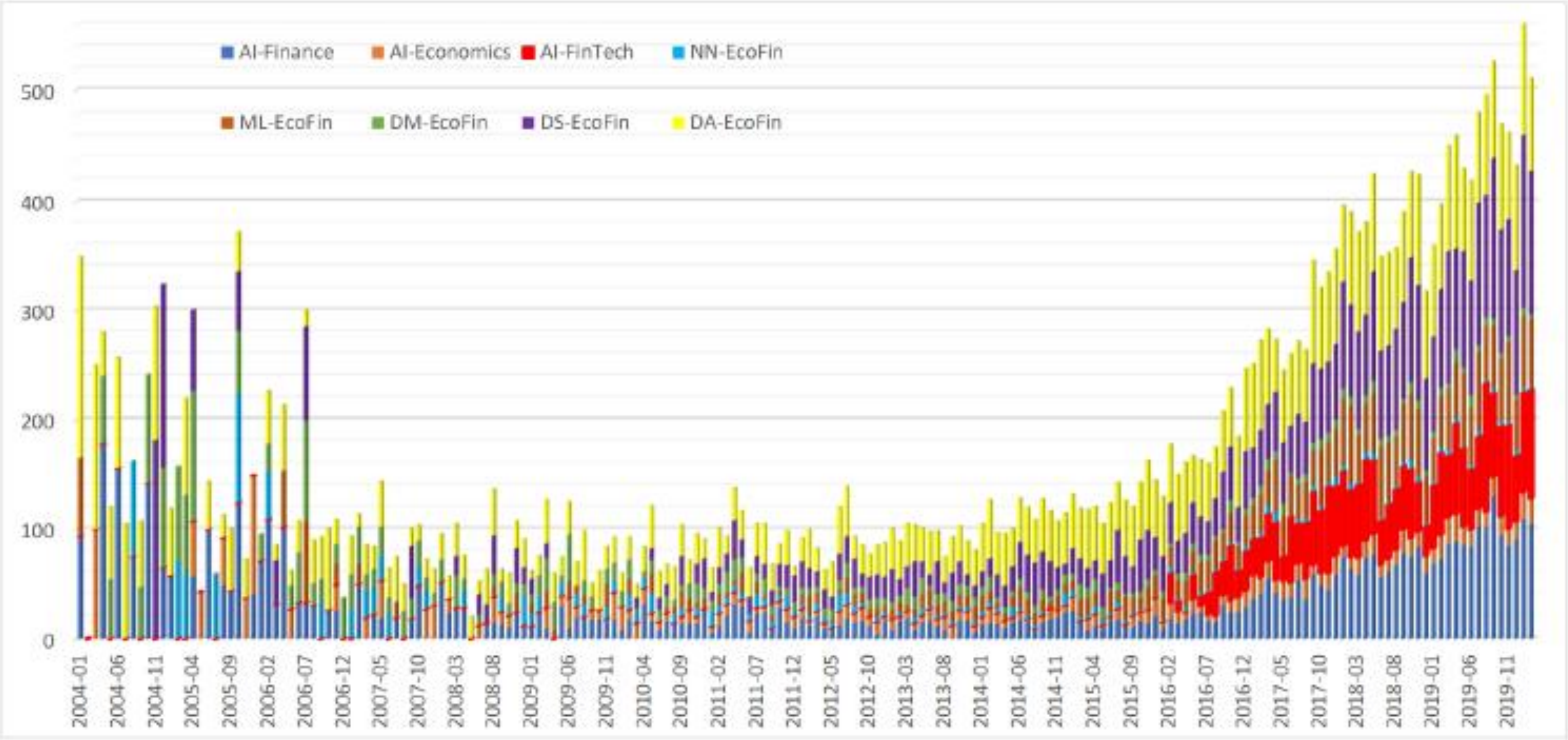
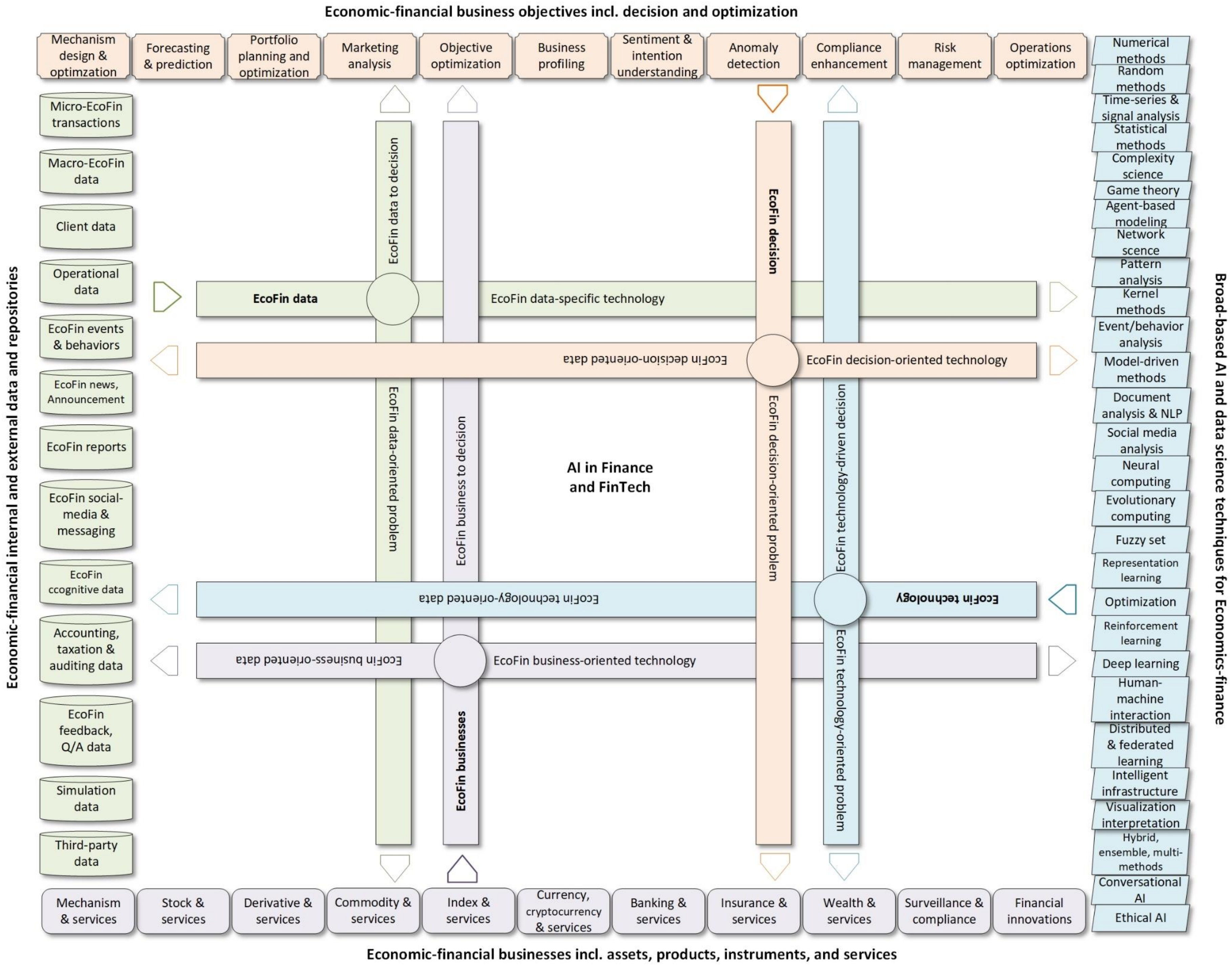


Fig. 1. The Google search trend of AIDS-related areas in/for finance and economics between Jan. 2004 and Feb. 2020.



An Overview of AI in FinTech

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AI in Finance: A Review

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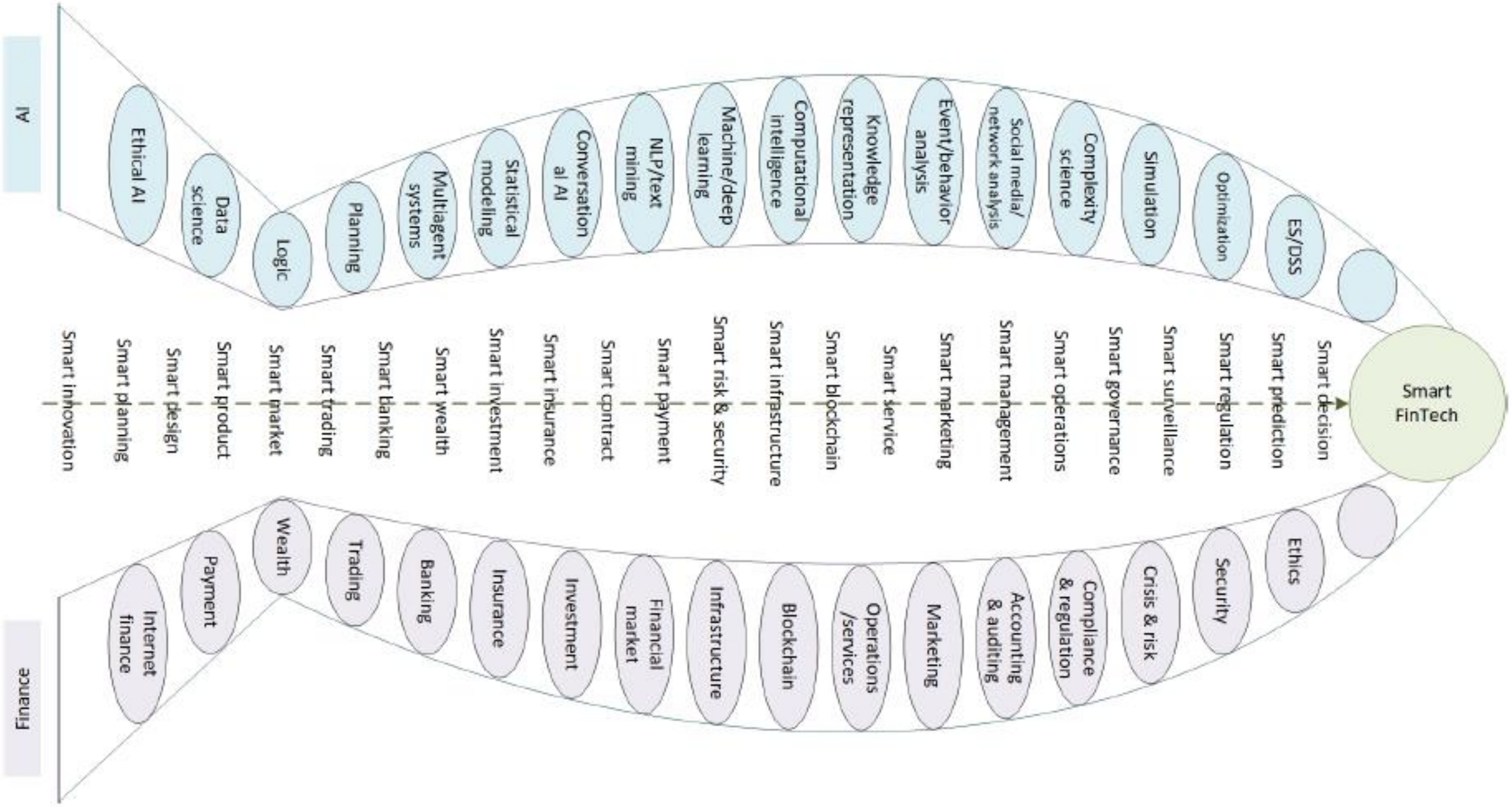


Fig. 1. The Synthesis between AIDS Techniques and Financial Businesses That Forms *Smart FinTech*. The upper fin refers to broad AIDS areas and techniques, the lower fin consists of major financial areas, and the ridge includes various synthetic areas of smart FinTech.

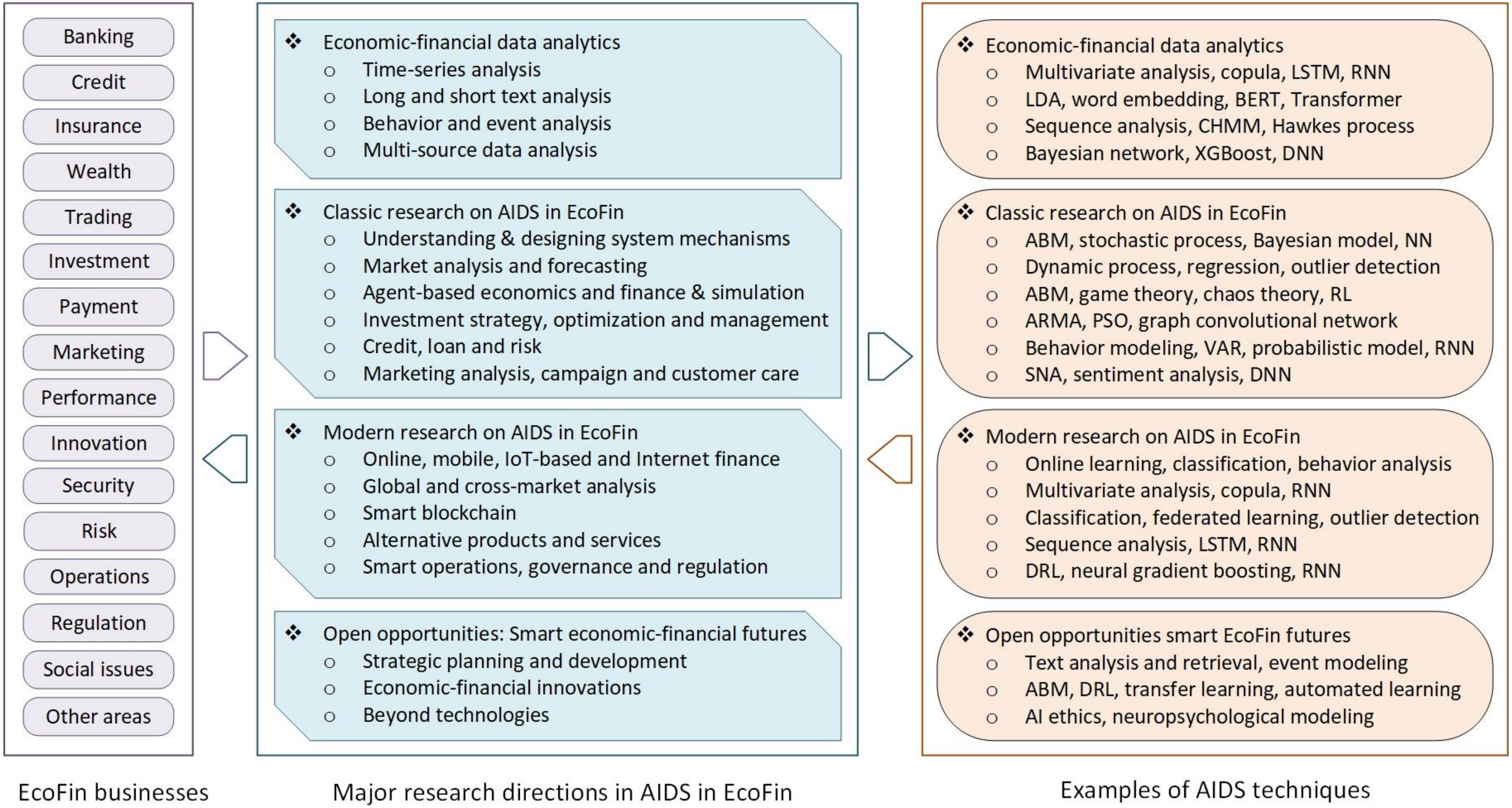


Fig. 3. The research areas of AIDS for smart EcoFin and FinTech.

Table 1. AIDS Techniques and Their Representative Applications in Finance.

AIDS areas	AIDS methods	Applicable EcoFin problems
Mathematical and statistical modeling	Numerical methods	Valuation, pricing, portfolio simulation and optimization, capital budgeting, hedging
	Time-series and signal analysis	Price prediction, market movement, IPO prediction, equity-derivative correlation analysis
	Statistical learning methods	Price estimation, VaR forecasting, financial variable dependency modeling, portfolio performance estimate
	Random methods	Abnormal behavior analysis, market event analysis, influence transition analysis, associated account analysis
Complex system methods	Complexity science methods	Market simulation, mechanism design, globalization analysis, crisis contagion, market information flow
	Game theory methods	Policy simulation, regional conflict, mechanism testing, and cryptocurrency mechanism testing
	Agent-based modeling	Testing economic hypotheses, simulating policies, supply/chain relations, portfolio optimization
	Network science	Modeling entity movement, community formation, interactions and linkage, influence and contagion propagation
Classic analytics and learning methods	Pattern mining methods	Trading behavior analysis, abnormal trading, outlier detection, investor relation analysis
	Kernel learning methods	Price and market movement prediction, cross-market analysis, financial crisis analysis, crowdfunding estimate
	Event and behavior analysis	Financial event analysis, price co-movement, abnormal behavior analysis, market event detection
	Document analysis, text mining, and NLP	Financial event analysis, sentiment analysis, company valuation, financial reporting and review, auditing, fake news and misinformation analysis
	Model-based methods	Hypothesis testing, index modeling, event analysis, fraud detection, movement forecasting
	Social media and network analysis	Social influence analysis, sentiment analysis, opinion modeling, customer feedback analysis, market and price movement, associate account detection, detecting manipulation and insider trading
Computational intelligence methods	Neural computing methods	Macroeconomic and microeconomic factor correlation, valuation, portfolio optimization
	Evolutionary computing methods	New product simulation, financial objective optimization, market performance optimization
	Fuzzy set methods	Modeling market momentum, financial solvency, risk and capital costs
Modern AIDS methods	Representation learning	Representation of stocks, assets, markets, portfolios, events, behaviors, and financial reports
	Short and informal text analysis	Text-based trend forecasting of price, market, sentiment and reputation, question/answering
	Optimization methods	Optimizing policies, portfolios, trading strategies, VaR, and market performance
	Reinforcement learning methods	Simulating and optimizing supply/demand of new assets and services, discovering trading signals, portfolios and investment actions, optimizing portfolios and trading strategies
	Deep learning methods	Market modeling, behavior modeling, trading modeling, risk analysis, price and movement prediction
Hybrid AIDS methods	Parallel ensemble	Price and market movement forecasting, risk analysis, financial event detection, customer profiling,
	Sequential and hierarchical hybridization	Financial review-based fraud detection, macroeconomic influence on market movement, social media impact on price movement, epidemic evolution and impact on market volatility, trend and confidence
	Cross-disciplinary hybridization	Psychological factors and irrational market behaviors, behavioral economics and finance, sentiment and intention modeling, misinformation and mispricing on market inefficiency

Table 1. Classic AI Techniques and Their Representative Applications in Finance.

AI areas	Financial areas	Typical financial problems	Typical AI methods
Modeling economic-financial mechanisms	Understanding financial systems	Modeling market ecosystem, pricing, hypotheses, relations, interactions, trading, movement, and marketing mechanisms, processes, and effect, etc.	Mathematical modeling, statistical modeling, quantitative analysis, game theories, theories of complex systems, simulation, machine learning, etc.
	Artificial financial markets	Simulating and testing market mechanisms, models, policies, new products and services, trading rules, regulation, stakeholder relations and interactions, etc.	Computer simulation, agent-based modeling, game theories, theories of complex systems, human machine interaction, optimization methods, reinforcement learning, etc.
Financial market analysis and forecasting	Market complexities and dynamics	Modeling financial system characteristics; macro, meso and micro indicators and variables; interactions, information and influence propagation and effect; etc.	Quantitative and quantitative modeling, complex systems, information theory, network theories, data analytics, machine learning, etc.
	Financial time-series analysis	Modeling and predicting market movement, trend, volatility dynamics, exceptions, events, etc.	Time-series analysis, sequence analysis, pattern mining, dynamic process and programming, machine learning, and deep models, etc.
	Trading design and optimization	Discover and optimize strategies, signals and movements for pricing, trading, portfolio, and risk management, etc.	Quantitative analysis, data mining, machine learning, behavior analysis, risk analytics, and optimization methods, etc.
	Financial relation and interactions	Characterizing and analyzing diversified, hierarchical and multidimensional relations and interactions in financial variables and participants, etc.	Mathematical modeling, statistical modeling, relation learning, interaction learning, network theories, graph theories, etc.
	Market anomaly analysis	Recognize and predict abnormal movements, trends, behaviors, events inside/outside markets and of participants, etc.	Outlier detection, novelty/exception/change detection, behavior analytics, pattern mining, event modeling, probabilistic modeling, clustering, and classification, etc.
Agent-based economics and finance	Agent-based modeling	Modeling and simulating markets, supply and demand, participant behaviors and relations, mechanisms, policies, strategies, emergence and effect, etc.	Multiagent systems, simulation theories, human computer interaction, user modeling, behavior modeling, visualization, etc.
	Agent-based economics	Simulating macro/micro-economic hypotheses, policies, protocols, mechanisms and their effect in multiagent systems, etc.	Multiagent systems, computational economics and finance, and computational experiments, etc.
Intelligent investment, optimization and management	Automated and smart investment	Developing and optimizing intelligent investment models, algorithms, platforms and services with market forecasting and risk-averse management, etc.	Market representation, forecasting, portfolio optimization, learn to rank, reinforcement learning, recommender systems, behavior analysis, deep models, game theories, optimization methods, etc.
	Online and offline portfolio optimization	Selecting, optimizing and managing online or offline diversified forms and products of portfolios with market prediction and risk management, etc.	Market representation, prediction, learn to rank, game theories, reinforcement learning, recommender systems, behavior analysis, deep models, portfolio optimization, optimization methods, etc.
Intelligent credit, loan and risk management	Credit management	Estimating, predicting and optimizing credit rating, limit, valuation, scheduling, and risk and fraud management, etc.	Profiling, forecasting, prediction, sequential and recurrent modeling, game theory, reinforcement learning, behavior analytics, risk analytics, optimization, etc.
	Loan management	Estimating, predicting and optimizing loan value, default, refund, repayment, refinance, risk and fraud management, etc.	Profiling, forecasting, prediction, behavior informatics, sequence analysis and modeling, game theory, reinforcement learning, risk analytics, and optimization, etc.
	Risk management	Modeling, predicting and managing risk factors, effect and its severity, fraud, crime, security-related events and money laundering associated with diversified financial products, mechanisms, markets and participants, etc.	risk analytics, probabilistic modeling, classification, clustering, semi-supervised learning, behavior modeling, sequential modeling, event analysis, deep neural models and reinforcement learning, etc.
Intelligent marketing	Marketing analysis and campaign	Analyzing marketing performance, product/company competitiveness, campaign effect, competitor advantage and strategies, market share change, recommending and optimizing marketing campaign strategies, actions, and target, etc.	Numerical modeling, econometrics, forecasting, prediction, event analysis, behavior analysis, interaction analysis, game theories, reinforcement learning, recommender systems, optimization methods, etc.
	Customer management	Understanding and predicting customer needs, sentiment, satisfaction, concerns, complaints, circumstance change, new demand, potential churning, mitigation strategies, etc.	Profiling, prediction, interaction modeling, behavior analytics, change analysis, social media analysis, text analysis, and recommender systems, etc.

Table 2. Modern AI Techniques and Their Representative Applications in Finance.

AI areas	Financial areas	Typical financial problems	Typical AI methods
Intelligent online, mobile, IoT-based and Internet finance	Intelligent e-commerce	Estimating, predicting and optimizing online pricing, demand, supply, production, storage, logistics, delivery, marketing, risk, fraud, security, etc.	Profiling, predictive modeling, network analysis, web analysis, social media analysis, text analysis, distributed learning, behavior analytics, user modeling, interaction modeling, trajectory modeling, recommender systems, risk analytics, etc.
	Smart banking and payment	Supporting smart, secure and risk-averse online/mobile and other banking and payment methods, tools, behaviors and services; analyzing and predicting banking and payment demand, trend, growth, risk, fraud, security, malfunctions, etc.	Various methods of data mining, machine learning, deep learning, distributed learning, recommender systems, behavior informatics, risk analytics, security informatics, etc.
	Internet finance	Automating, predicting, securing and optimizing Internet-based financing, investment, wealth management, trust, credit, insurance, payment, etc.	Online/web/network analysis, online user modeling, interaction modeling, behavior analytics, text analysis, prediction, distributed learning, recommender systems, outlier detection, risk analytics, etc.
Global and cross-market analysis	Macro/micro-economic analysis	Coupling and analyzing the interactions, relations and influence between macroeconomic variables/markets and micro-financial variables; and modeling and predicting the influence of one level on the movement of the other level of financial markets or variables, etc.	Mathematical modeling, statistical modeling, multi-source/modal/view analysis, coupling learning, hybrid methods, event analysis, behavior analysis, interaction learning, etc.
	Cross-market analysis	Modeling relations, interactions and influence between financial (e.g. underlying-derivative) markets, regions, countries, companies and financial indicators; modeling relations and influence of economic, social, cultural and political aspects on financial markets; modeling financial crisis, influence and contagion; etc.	Multivariate analysis, dependence modeling, coupling learning, relation learning, interaction learning, multi-source/modal/view analysis, event modeling, behavior analysis, sequence modeling, hybrid methods, etc.
Intelligent blockchain	Blockchain systems and mechanisms	Modeling blockchain system complexities to optimize blockchain mechanisms and design; evaluating and optimizing bitcoin and cryptographic contracts and models; optimizing pricing and portfolio; etc.	Theories of complex systems, game theories, representation learning, agent-based modeling, reinforcement learning, machine learning, deep learning, distributed learning, online learning, behavior analytics, prediction, semantic web, optimization methods, etc.
	Blockchain security	Enabling secure, privacy-preserving, risk-averse and anti-attack blockchain systems and smart contracts; detecting and mitigating malicious attacks and criminal activities; assuring active governance and regulation; etc.	Process analysis, event analysis, behavior analytics, outlier detection, change detection, distributed learning, risk analytics, security data analytics, fraud detection, and benchmarking, etc.
Smart alternative finance	Property market	Estimating and predicting property valuation, pricing, demand, supply, recommendation and site selection; evaluating and optimizing property policies and governance; etc.	Numerical computing, machine learning, statistical learning, data mining, knowledge discovery, evolutionary computing, text analysis, social media analysis, behavior analytics, recommender systems, etc.
	Insurance	Estimating, predicting, optimizing and recommending insurance products and services and their pricing and market positioning; personalized product customization and recommendation; detecting fraud and risk; etc.	Profiling, classification, statistical modeling, mathematical modeling, outlier detection, behavior analysis, sequence modeling, interaction learning, and document analysis, social media analysis, risk analytics, recommender systems, deep learning, etc.
	Foreign exchange market	Predicting currency rating and movement; optimizing currency portfolio and cross-marketing trading; analyzing cross-market movement and influence; etc.	Multivariate time series, artificial neural network, evolutionary computing, coupling learning, multi-source/modal analysis, cross-market analysis, influence modeling, behavior analysis, and event analysis, etc.
	Energy	Estimating, predicting and optimizing the pricing, movement, supply, demand of electricity, oil, solar, gas, wind, nuclear and water power; optimizing energy pricing, marketing, service and portfolio; etc.	Machine learning, optimization methods, knowledge discovery, forecasting and prediction techniques, anomaly and exception analysis, coupling learning, and dependency modeling, etc.
	Wealth management	Discovering wealthy people and demand; recommending personalized products, services and customer care; detecting circumstance change and new requirements; customizing risk management, training and social trading services; etc.	Customer profiling, behavior analysis, sentiment analysis, prediction, active learning, intent learning, capability and propensity modeling, personalized recommendation, knowledge engineering, etc.
Optimal operations, governance and regulation	Smart operations and regulation	Evaluating and optimizing operation, governance and regulation performance; discovering factors, problems, failures, low-performing areas, risk and loss of operations and governance; analyzing operational, financial, regulatory, personnel and service risk; etc.	Process analysis, risk analytics, behavior analytics, event analysis, interaction modeling, relation learning, multi-source/modal analysis, prediction techniques, outlier detection, etc.
	Corporate finance	Analyzing, predicting and optimizing corporate financial budget, balance, accounting integrity, auditing issues, and payment accuracy; detecting and mitigating financial fraud, overpayment, irregular behaviors and activities, and risk; etc.	Financial time series analysis, numerical optimization, anomaly detection, probabilistic learning, relation learning, risk analytics, representation learning, and supervised and unsupervised learning, etc.

Table 3. Mathematical and Statistical Techniques and Their Pros and Cons in Financial Applications.

Techniques	**Methods**	**Pros in finance**	**Cons in finance**
Numerical methods	Linear and nonlinear equations, least square problem, finite difference methods, dependence modeling, Monte-Carlo simulation, etc.	Model-driven, hypothesis testing, and forecasting; mathematically modeling determinant financial processes, mechanisms and dynamics; analytic or approximate results and interpretation; etc.	Complex processes, mechanisms and dynamics; high-dimensional/order and low-quality (e.g., missing, incomplete, inconsistent) data; nonstationary, heterogeneous, dynamic, uncertain and large data; population size; etc.
Time-series and signal analysis	State space modeling, time-series analysis, spectral analysis, long-memory time-series analysis, nonstationary analysis, etc.	Modeling temporal processes, relations, dynamics and effects; trends, movements, changes and forecasting; multivariate relations and movements; etc.	Non-temporal, multiple and heterogeneous relations, processes and dynamics; mixed factors, data, relations and processes; poor data quality (e.g., noise) and stylist effects; structure and sample dynamics and nonstationarity; overfitting; population size; etc.
Statistical learning methods	Random walk models, factor models, stochastic volatility models, copula methods, nonparametric methods, etc.	Model-driven and hypothesis testing; sampling; latent variables, relations and models; dependency, uncertainty and randomness; probabilistic interpretability; etc.	Modeling other and mixed relations, processes and dynamics; mixed observable data; poor-quality data; large data and scalability; result actionability; etc.
Random methods	Random sampling, random walk models, random forest, stochastic theory, fuzzy set theory, quantum mechanics, etc.	Modeling random processes, relations and dynamics; randomness, uncertainty, fuzziness; fair and unbiased representativeness; etc.	Too small or large populations; complex (e.g., imbalanced, unequal) data; dynamic data; mixed data complexities; bias and error; etc.

Table 4. Theories of Complex Systems and Their Pros and Cons in Financial Applications.

Techniques	**Methods**	**Pros in finance**	**Cons in finance**
Complexity science	Systems theory, complex adaptive systems, chaos theory, random fractal theory, etc.	Modeling system complexities; simulating complex financial processes, mechanisms, and characteristics; incorporating social science; trial and test; etc.	Incomplete and limited understanding; mixing qualitative and quantitative factor modeling; evaluation and optimization; etc.
Game theory	Zero-sum game, differential game, combinatorial game, evolutionary game, Bayesian game, etc.	Hypothesis testing; rule-based design; scenario analysis; trail and test; involving reinforcement learning; etc.	Complex design and interactions; involving financial rules, theories and measures; complex financial characteristics; etc.
Agent-based modeling	Multiagent systems, belief-desire-intention model, reactive model, swarm intelligence, reinforcement learning, etc.	Rule-based modeling and controlled experiments; simulation; self-organizing mechanisms; mechanism testing; etc.	. Complex financial scenarios; runtime behaviors and decision-making; dynamics; quantitative and formal modeling; etc.
Network science	Linkage analysis, graph methods, power law, small worlds, contagion theory, etc.	Modeling networking modes, interactions and processes; social influence; visualization; etc.	Complex interactions, relations and processes; heterogeneous and high-dimensional financial systems and mechanisms; multi-aspects, sources and modalities; etc.

Table 5. Classic Analytics and Learning Methods and Their Pros and Cons in Financial Applications.

Techniques	Methods	Pros in finance	Cons in finance
Pattern mining methods	Frequent itemset mining, sequence analysis, combined pattern mining, high-utility pattern mining, tree pattern, network pattern, knot pattern, interactive pattern, etc.	Extracting and recognizing patternable structures, modes and relations; interpretability; actionable rules; etc.	Infrequent events and behaviors; high false positive; missing important financial events and activities; relations and interactions; etc.
Kernel learning methods	Vector space kernel, tree kernel, support vector machine, spectral kernel, Fisher kernel, nonlinear kernel, multi-kernel methods, etc.	Kernel tricks for complex problem modeling; scalable; metric properties; etc.	Kernel selection; calibration; training; interpretability; and actionability; etc.
Event and behavior analysis	Sequence analysis, Markov chain process, high-impact behavior, high-utility behavior, nonoccurring behavior analysis, etc.	Modeling financial events, processes, interactions, and activities; sequential modeling; event/behavior impact; simulation; visualization; actionable; etc.	Complex processes, interactions and behaviors; insufficient event/behavior modeling theories and tools; mixed and dynamic processes; uncertainty and change; predictive consequences; etc.
Document analysis and NLP	Language models, case-based reasoning, statistical language model, Bayesian model, latent Dirichlet allocation, Transformer, BERT, etc.	Linguistic and semantic representation and analysis; unstructured data; long and short text; subjective and objective factors; sentiment; opinion; etc.	Complex syntactic and semantic relations and structures; expression informality; financial knowledge embedding; multi-linguistic interactions and heterogeneities; scalability; etc.
Model-based methods	Probabilistic graphical model, Bayesian networks, expectation-maximization model, clustering, classification, deep neural models, etc.	Hypothesis testing; modeling design-based processes, behaviors and dynamics; paradigm and modeling tools-dependent; wide applicability; etc.	Runtime and dynamic modeling; handcrafting issues; model selection; under/over-fitting; financial semantics and knowledge; financial explanability; etc.
Social media analysis	Topic modeling, sentiment analysis, emotional analysis, influence analysis, linkage analysis, interaction learning, etc.	Modeling financial events, sentiments and opinions; social activities, interactions and influence; etc.	Misinformation; bias; mixed financial data and information; financial mechanisms, processes and systems; etc.

Table 6. Computational Intelligence Methods and Their Pros and Cons in Financial Applications.

Techniques	**Methods**	**Pros in finance**	**Cons in finance**
Neural computing methods	Wavelet neural network, genetic neural network, recurrent neural network, deep neural network, etc.	Simulating human neural and cognitive systems and mechanisms; complex relations and structures; incomplete input; data-driven modeling; fault-tolerance; distributed/parallel processing; hierarchical processing; great learning performance; etc.	Limited to neural mechanisms; other complex processes and mechanisms; network structure selection; parameterization; overfitting; computation-intensive; interpretability; actionability; etc.
Evolutionary computing methods	Ant algorithm, genetic programming, self-organizing map, artificial immune system, swarm intelligence, neural-genetic algorithm, etc.	Simulating evolutionary and genetic systems and mechanisms; financial simulation; optimization; exploratory results; etc.	Limited to evolutionary mechanisms; bias in local/global optimal and extremum; configuration and parameter tuning; etc.
Fuzzy set methods	Fuzzy set theory, fuzzy logic, fuzzy neural network, genetic fuzzy logic, etc.	Modeling uncertain, imprecise, fuzzy and contradictory inputs; contradictory objectives; linguistic support; rule/symbol-based interpretation; etc.	Modeling limit; fine tuning; approximation; data-driven modeling; complex financial mechanisms, relations and processes; etc.

Table 7. Modern AI Techniques and Their Pros and Cons in Financial Applications.

Techniques	Methods	Pros in finance	Cons in finance
Representation learning	Probabilistic model, graph network, network embedding, tree model, neural embedding, etc.	Characterizing intrinsic characteristics and relations; discovering discriminative features and representations; various methods; enabling learning tasks; etc.	Representation constraints; curse of dimensionality, relation, interaction and heterogeneity; unsupervised learning; interpretability; etc.
Short and informal text analysis	Conceptualization, term/tag/phrase similarity learning, dependency parsing, word embedding, deep neural models, etc.	Analyzing informal communications and presentations; contextual and sequential presentations; linguistic specificity; etc.	Informality complexities; limited information; noise and misinformation; uncertainty and inconsistency; etc.
Optimization methods	Nonlinear, stochastic and dynamic programming, information theory, Bayesian optimization, etc.	Theoretical guarantee of correctness and generalization; hypothesis and setting specific; optimal results; etc.	Constraint; approximation; local/global optimum; computational complexity; applicability in complex financial systems; etc.
Reinforcement learning	Bellman Equation, actor-critic model, Markov dynamic progress, deep Q-network, adversarial reinforcement learning, etc.	Learning from mistake and correcting error until perfection; scenario/context-based policy and action optimization; modeling interactions; balancing exploration and exploitation; etc.	Markovian assumption; data and computation-hungry; scenario and policy specific; long-term dilemma; curse of dimensionality and samples; etc.
Deep learning methods	Convolutional neural network, attention network, generative adversarial network, autoencoder, deep Bayesian network, etc.	Deep abstraction and representation; powerful learning architectures; complex hidden relations and interactions; domain knowledge and supervised information; impressive learning performance; etc.	Data and computation-intensive; observable and explicit financial complexities; robustness; interpretability; actionability; etc.
Deep financial modeling	Deep neural networks, deep reinforcement learning, deep language learning, hybrid DNN with ARIMA, GARCH and copula etc. classic financial models, federated learning, etc.	Deep representation and learning of correlations, dependencies and temporal developments between financial factors and across financial markets and sectors	Vulnerability of modeling small financial data with asymmetric, non-normal, nonstationary and abruptly evolving features, heterogeneous distributions, and hierarchical couplings within and between implicit and explicit factors, etc.

Table 8. Hybrid AI Techniques and Their Pros and Cons in Financial Applications.

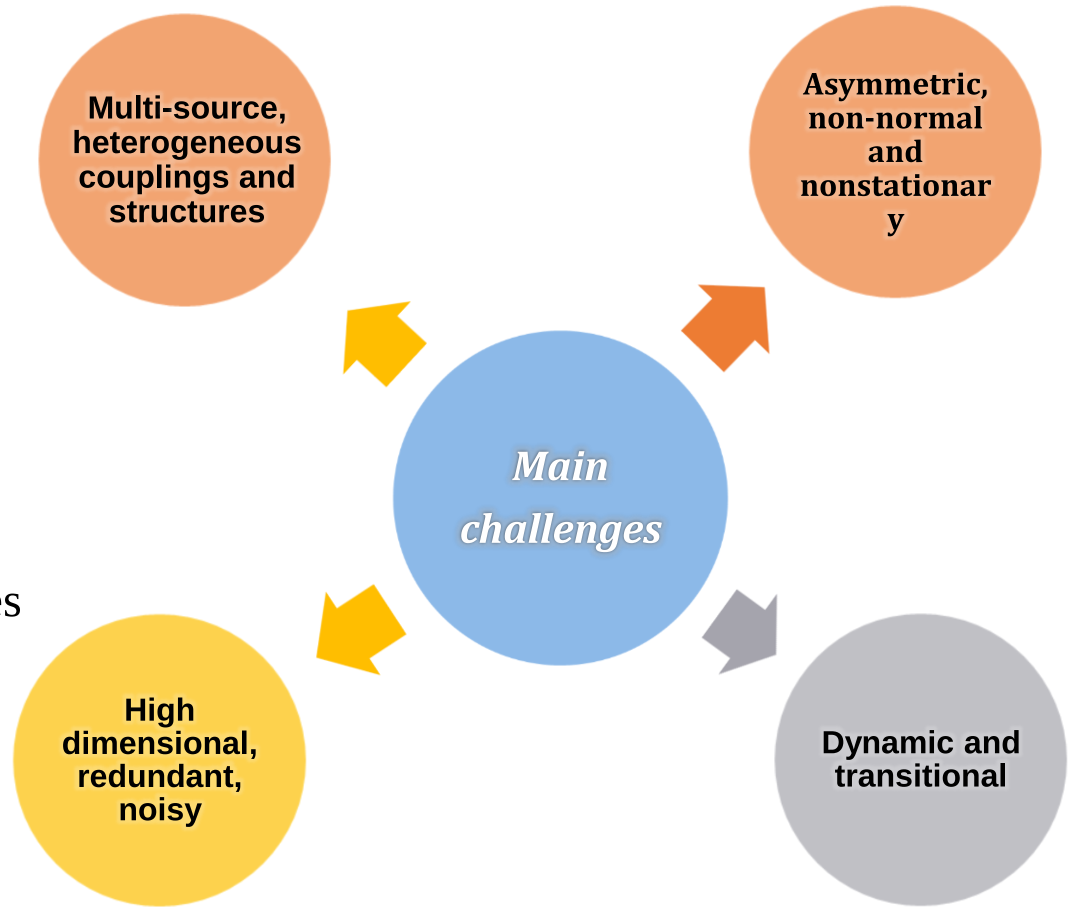
Techniques	Methods	Pros in finance	Cons in finance
Parallel ensemble	Evolutionary neural models, ensemble learning, deep Bayesian model, copula graph neural network, combining complexity science and game theory, etc.	Jointly modeling two to more financial aspects; integrating model capabilities; wide applicability in finance; better performance; etc.	Model selection and integration; compatibility; customized modeling process and structure; problem/task-specific; complexity; etc.
Sequential and hierarchical hybridization	Time-series analysis plus classification, macro/micro-economic dependency modeling, deep sequential modeling-based event detection, etc.	Jointly modeling two to more financial aspects; enhanced modeling capabilities; multi-stage modeling; wide applicability in finance; better performance; etc.	Model selection and integration; compatibility; customized modeling process and structure; problem/task-specific; complexity; etc.
Cross-disciplinary hybridization	Deep multi-time series analysis, copula deep models, autoregression deep model, behavioral economics and finance, etc.	Jointly modeling two to more financial aspects; enhanced modeling capabilities; wide applicability in finance; better performance; etc.	Method selection and integration; compatibility; customized modeling process and structure; problem/task-specific; complexity; etc.
Behavioral economics and finance	Prospect theory, nudge theory, natural experiment, experimental economics, behavior informatics, intention learning, next-best action modeling, etc.	Modeling psychological drivers and insights of EcoFin behaviors; financial experiments; subjective and social factors; interactions, behaviors and actions; etc.	Generalized theories and tools; qualitative-to-quantitative modeling; objective and subjective modeling; scenarios and samples specific; predictive power; etc.

Some Examples of AI in Finance

Main challenges

Cross-market financial variables are heterogeneous, coupled w.r.t. various structures

Multi-markets are often embedded with nonlinear, non-normal, nonstationary and asymmetric couplings and dependencies

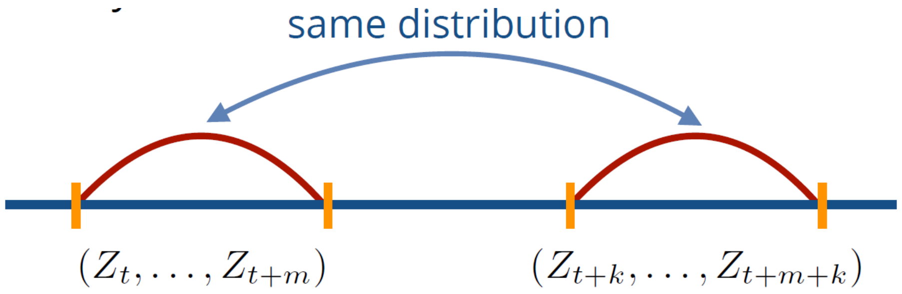


Many financial variables may be associated with very high-dimensional interactions that are explicit/implicit, strong/weak, global/local, etc.

Financial variables and their influence across markets are dynamic/ volatile, transitional, and evolving, etc.

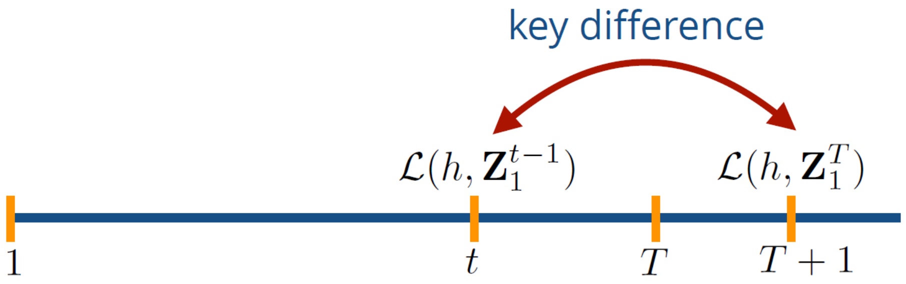
Nonstationarity

- Stationarity

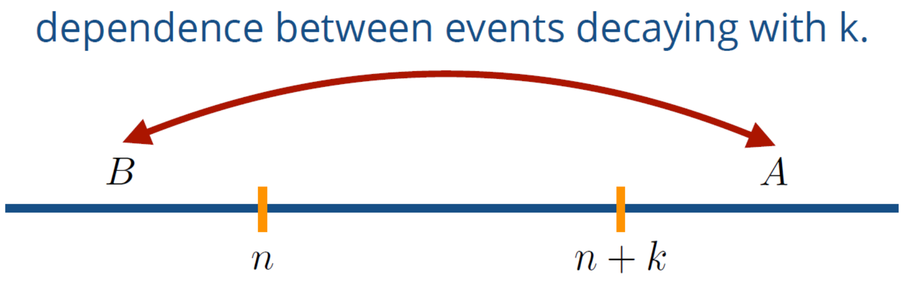


NIPS16 tutorial: Theory and algorithms for forecasting non-stationary time series

- Weak/non-stationarity



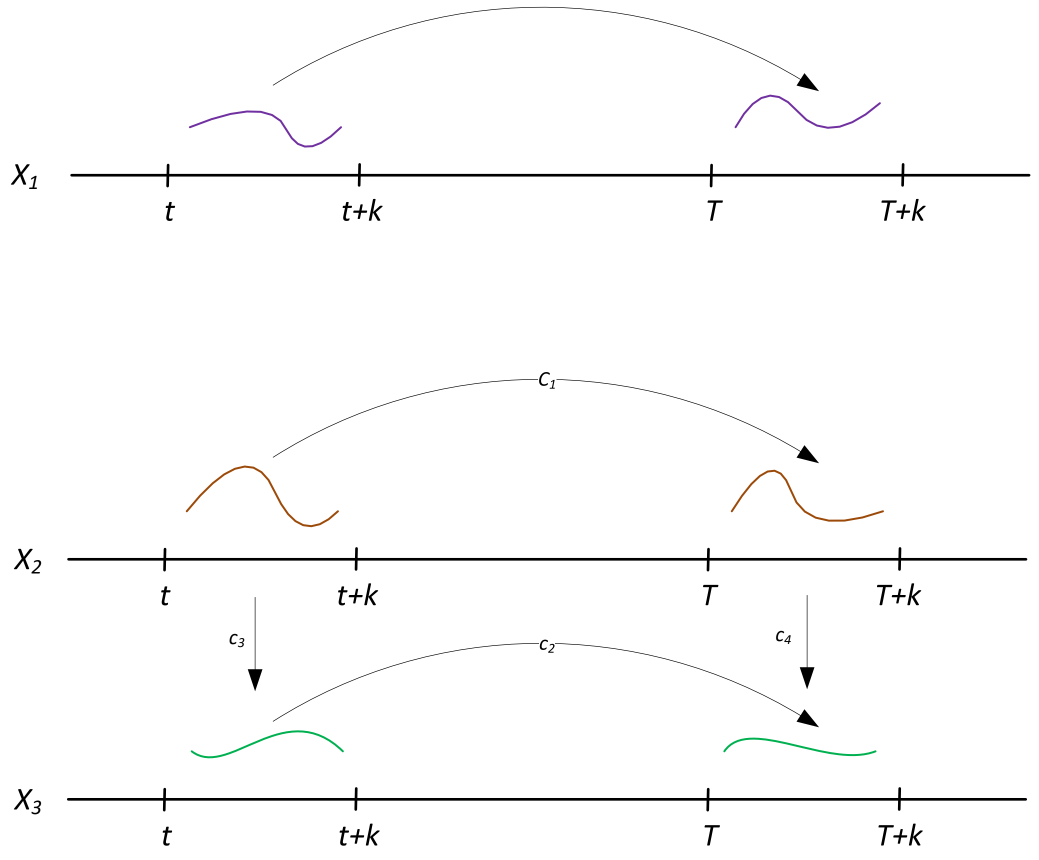
$$\Delta(\mathbf{q}) = \sup_{h \in H} \left| \mathcal{L}(h, \mathbf{Z}_1^T) - \sum_{t=1}^{T} q_t \, \mathcal{L}(h, \mathbf{Z}_1^{t-1}) \right|$$



$$\beta(k) = \sup_{n} \mathop{\mathbb{E}}_{B \in \sigma_{-\infty}^{n}} \left[\sup_{A \in \sigma_{n+k}^{\infty}} \Big| \mathbb{P}[A \mid B] - \mathbb{P}[A] \Big| \right] \to 0$$

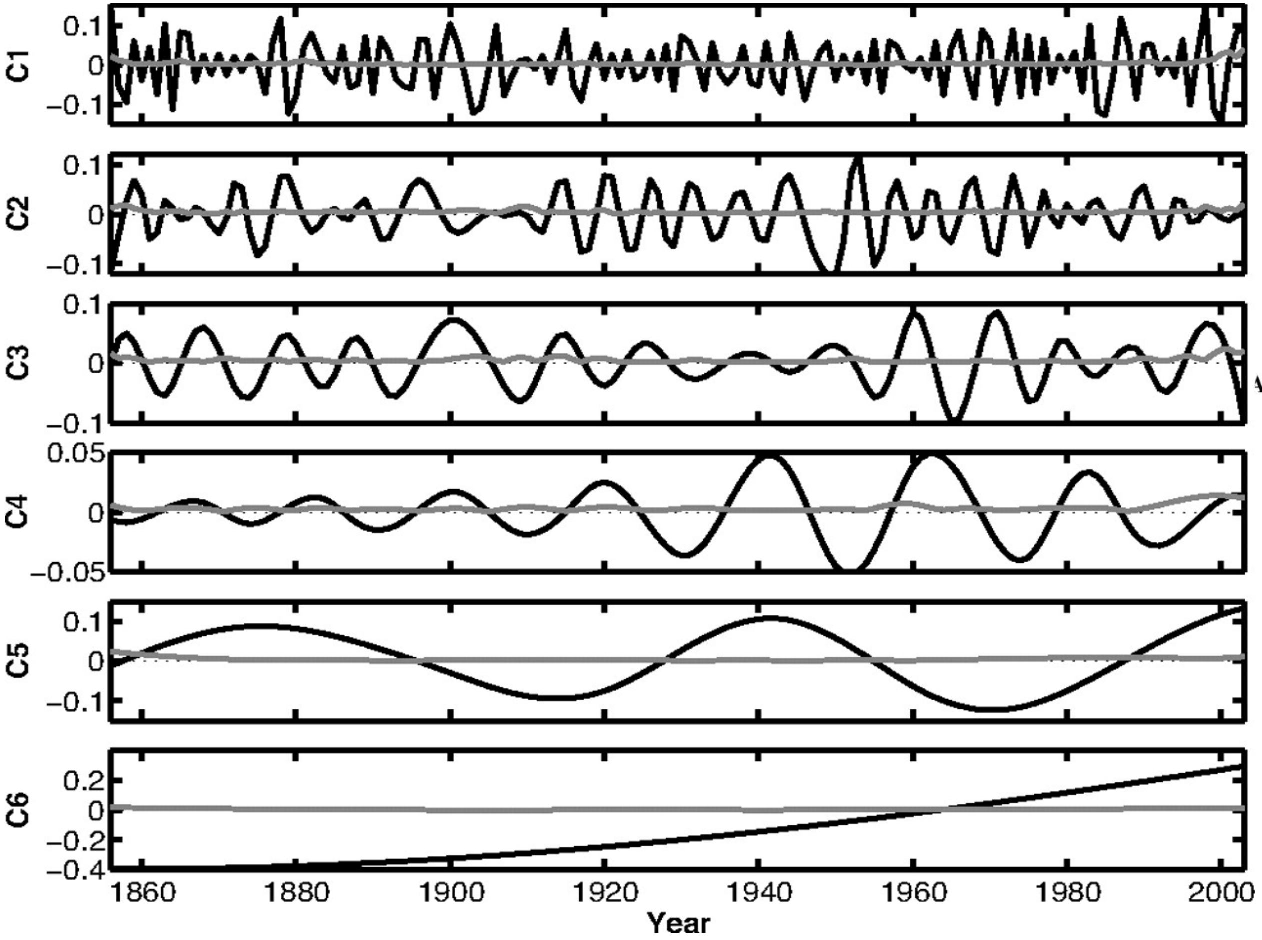
Nonstationary couplings

- The change of one nonstationary variable is coupled with the change of another one
- Couplings: Association, correlation, dependence, causality, latent relations, etc., which may be
  - Explicit/implicit, global/local, strong/weak, deep/shallow, subjective/objective, etc.



L Cao. Coupling Learning of Complex Interactions

Nonstationary heterogeneous couplings



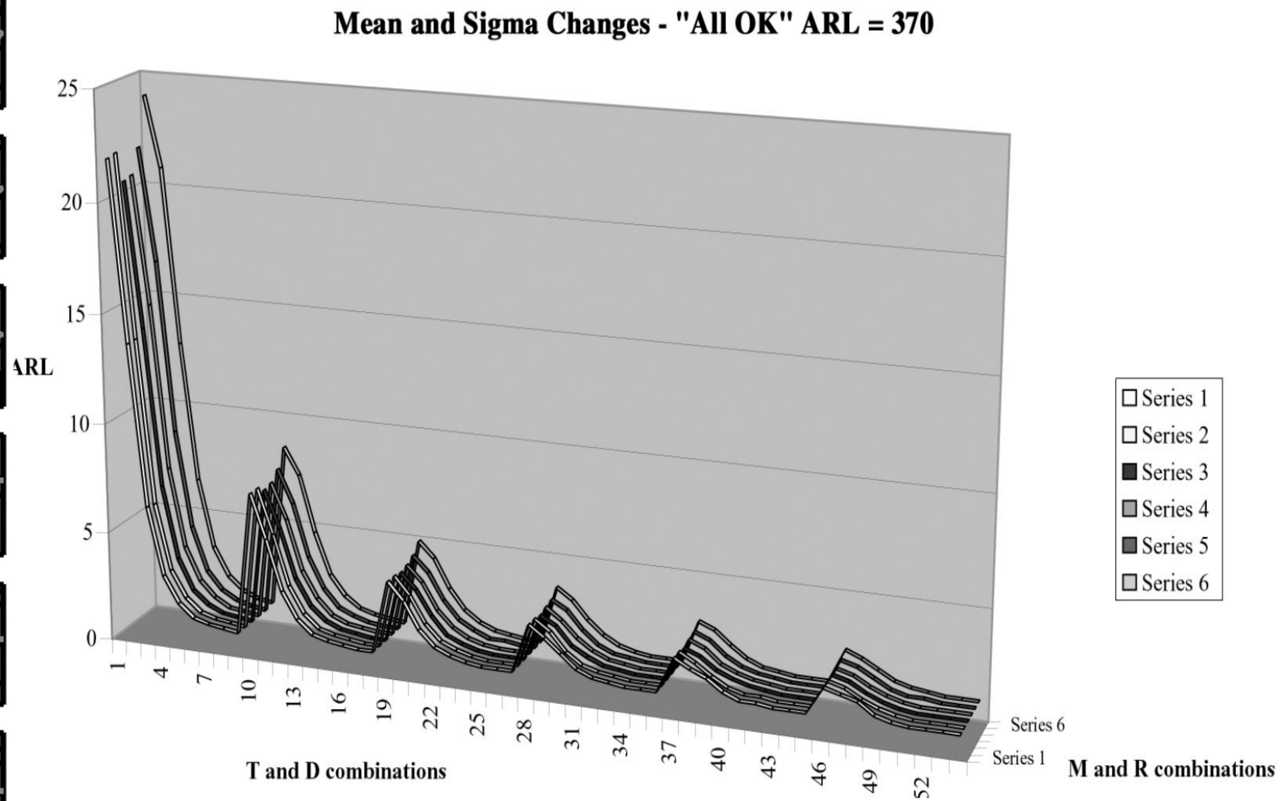
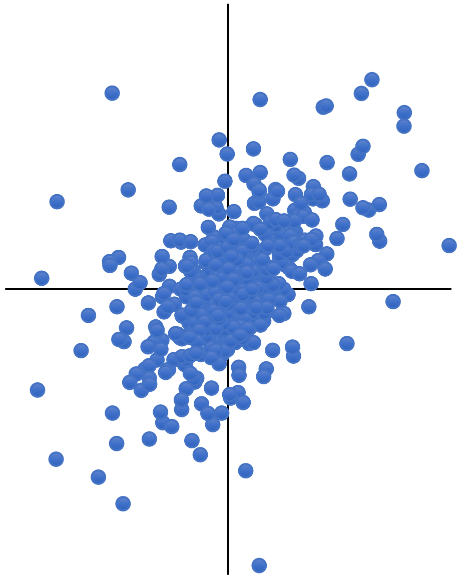


Figure 3. Plotted ARL values of Table 3.

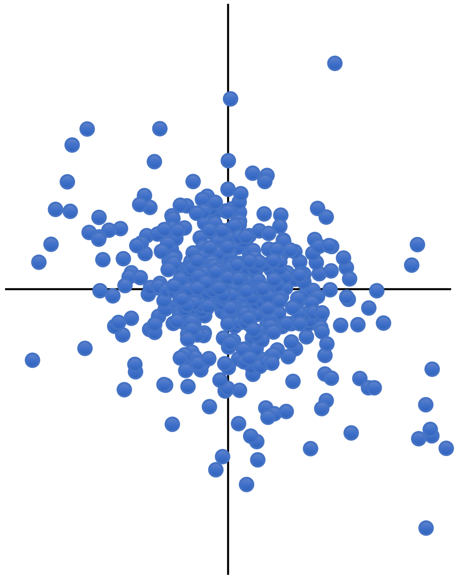
Z Wu, etc. (2007) On the trend, detrending, and variability of nonlinear and nonstationary time series

D. Rahardja (2005) X-Charts versus X / MR Chart Combinations: IID Cases and Non-IID Cases

Positive and negative correlations



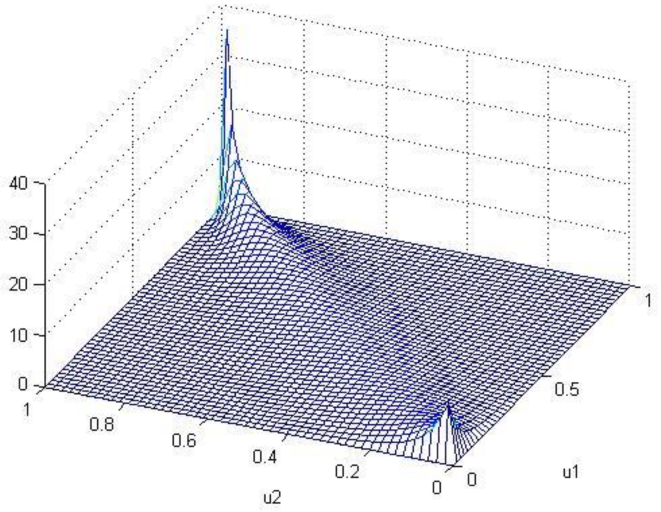
a. FTSE100 and S&P500



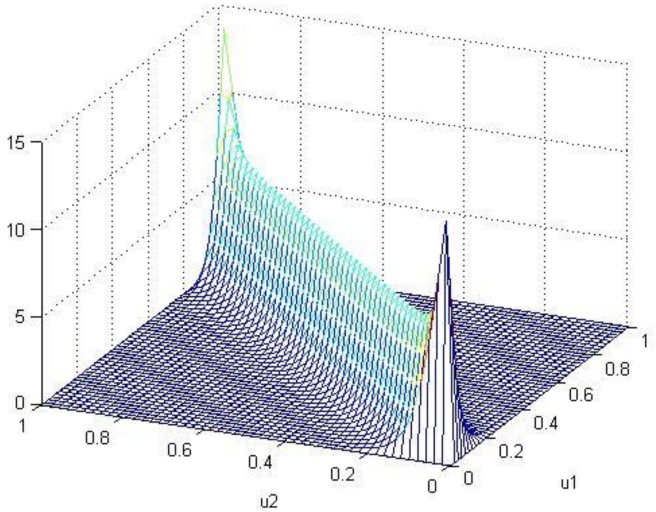
b. FTSE100 and GBP

- Stock markets and exchange rate markets are dependent
- Dependences may be diverse
- Cross-market couplings have to be considered in multivariate modeling

Asymmetric and tail dependence



Gumbel Copula (ϑ = 3.35) **between S&P500 and STOXX50E**



Frank Copula (ϑ = 28.5) **between** ***FTSE100 and GBP***

Daily returns of S&P 500 and EUR/USD (01/01/2008 – 31/12/2010)

Modeling Asymmetry and Tail Dependence among Multiple Variables by Using Partial Regular Vine

Example 1: Coupled Behavior Analysis for Pool Manipulation Detection

- Coupled Behavior Analysis with Applications
- Detecting Abnormal Coupled Sequences and Sequence Changes in Group-based Manipulative Trading Behaviors
- Coupled Behavior Analysis for Capturing Coupling Relationships in Group-based Market Manipulation
- Graph-based Coupled Behavior Analysis: A Case Study on Detecting Collaborative Manipulations in Stock Markets

Trading behaviors in stock tick data

Transactional Data → **Behavior Feature Matrix**

	Investor	Time	Direction	Price	Volume
B1	(1)	09:59:52	Sell	12.0	155
B2	(2)	10:00:35	Buy	11.8	2000
B3	(3)	10:00:56	Buy	11.8	150
B4	(2)	10:01:23	Sell	11.9	200
B5	(1)	10:01:38	Buy	11.8	200
B6	(4)	10:01:47	Buy	11.9	200
B7	(5)	10:02:02	Buy	11.9	250
B8	(2)	10:02:04	Sell	11.9	500

$$FM(\mathbb{B}) = \begin{pmatrix} B_1 & B_5 & \varnothing \\ B_2 & B_4 & B_8 \\ B_3 & \varnothing & \varnothing \\ B_6 & \varnothing & \varnothing \\ B_7 & \varnothing & \varnothing \end{pmatrix}$$

- Each behavior of an investor is a vector
- The collective behaviors form a temporal behavior vector matrix

Coupled behavior modeling

$$FM(\mathbb{B}) = \left(\begin{array}{cc|cc} \mathbb{B}_{11} & \mathbb{B}_{12} & \cdots & \mathbb{B}_{1J_{max}} \\ \mathbb{B}_{21} & \mathbb{B}_{22} & \cdots & \mathbb{B}_{2J_{max}} \\ \vdots & \vdots & \ddots & \vdots \\ \hline \mathbb{B}_{I1} & \mathbb{B}_{I2} & \cdots & \mathbb{B}_{IJ_{max}} \end{array}\right)$$

Intra-behavior couplings:

$$\mathbb{B}_{i\cdot}^{\theta} ::= \mathbb{B}_{i\cdot}(\mathscr{E}, \mathscr{O}, \mathscr{C}, \theta) | \sum_{j=1}^{J_{max}} \theta_j(\cdot) \odot \mathbb{B}_{ij} \quad (1)$$

$$|\theta_j(\cdot)| \geq \theta_0 \quad (2)$$

Inter-behavior couplings:

$$\mathbb{B}_{\cdot j}^{\eta} ::= \mathbb{B}_{\cdot j}(\mathscr{E}, \mathscr{O}, \mathscr{C}, \eta) | \sum_{i=1}^{I} \eta_i(\cdot) \odot \mathbb{B}_{ij} \quad (3)$$

$$|\eta_i(\cdot)| \geq \eta_0 \quad (4)$$

Coupled behavior modelling:

$$\mathbb{B}_c = (\mathbb{B}_{i_1 j_1}^{\theta})^{\eta} * (\mathbb{B}_{i_2 j_2}^{\theta})^{\eta} ::= \mathbb{B}_{ij}(\mathscr{E}, \mathscr{O}, \mathscr{C}, \mathscr{R}) | \sum_{i_1, i_2 = 1}^{I} \sum_{j_1, j_2 = 1}^{J_{max}}$$

$$f(\theta_{j_1 j_2}(\cdot), \eta_{i_1 i_2}(\cdot)) \odot (\mathbb{B}_{i_1 j_1} \mathbb{B}_{i_2 j_2}) \quad (5)$$

$$f(\cdot) ::= f(\theta(\cdot), \eta(\cdot)), \quad (9)$$

$$g(\cdot) | (f(\cdot) \geq f_0) \geq g_0 \quad (10)$$

CHMM-based CBA

$$Category : \{\frac{Actor_i - Operation_i}{Attributes_i} \xrightarrow{\eta} \frac{Actor_j - Operation_j}{Attributes_j}\}_{i,j=1;winsize}^{I,J} \tag{14}$$

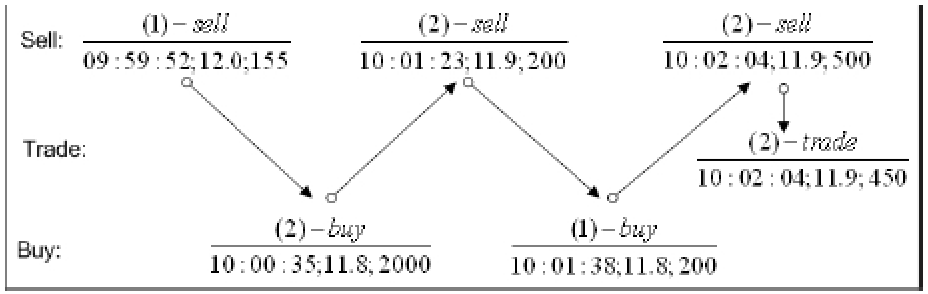
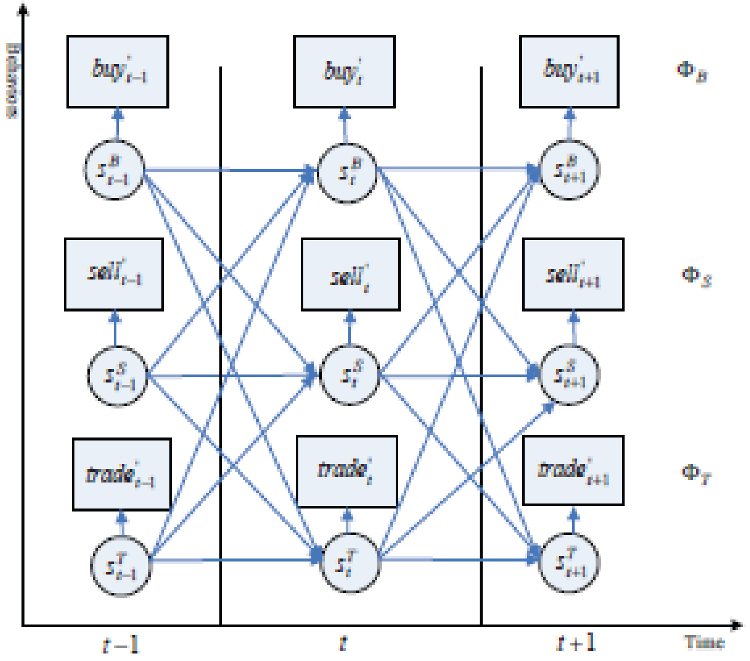


Fig. 3. Behavior sequences - Data Structure 2



(b) The Structure of the CHMM

$$CBA\ problem \rightarrow CHMM\ model \tag{15}$$

$$\Phi(\mathbb{B}_c)|category \rightarrow X \tag{16}$$

$$M(\Phi(\mathbb{B}_c))|\phi_{ik}([p_{ij}]_1, \ldots, [p_{ij}]_K) \rightarrow Y \tag{17}$$

$$f(\theta(\cdot), \eta(\cdot)) \rightarrow Z \tag{18}$$

$$Initial\ distribution\ of\ \Phi(\mathbb{B}_c)|category \rightarrow \pi \tag{19}$$

Framework: abnormal CBA

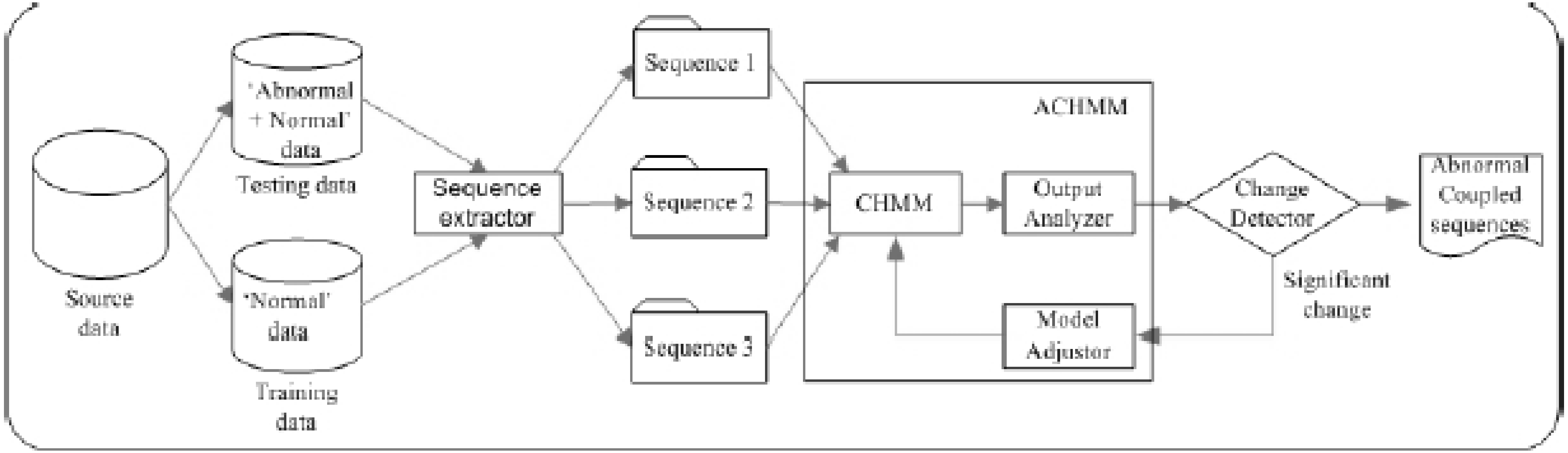


Fig. 5. Framework of abnormal coupled behavior detection

Figure 3: Update Point of ACHMM

$$x_{ij}^{update} = (1-w)x_{ij}^{old} + w * x_{ij}^{new} \quad (15)$$

$$y_{ij}^{update} = (1-w)y_{ij}^{old} + w * y_{ij}^{new} \quad (16)$$

$$z_{ij'}^{update} = (1-w)z_{ij'}^{old} + w * z_{ij'}^{new} \quad (17)$$

$$\pi_{i}^{update} = (1-w)\pi_{i}^{old} + w * \pi_{i}^{new} \quad (18)$$

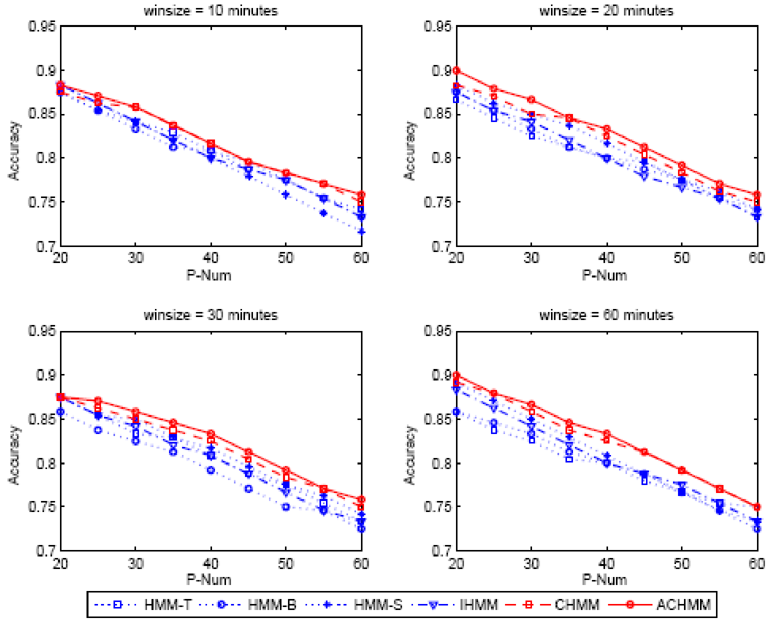


Figure 4: Accuracy of Six Models

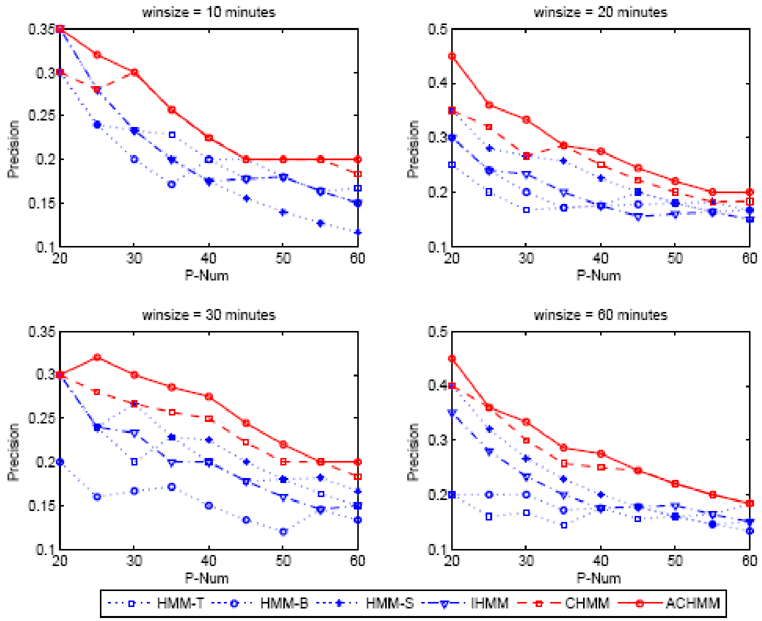


Figure 5: Precision of Six Models

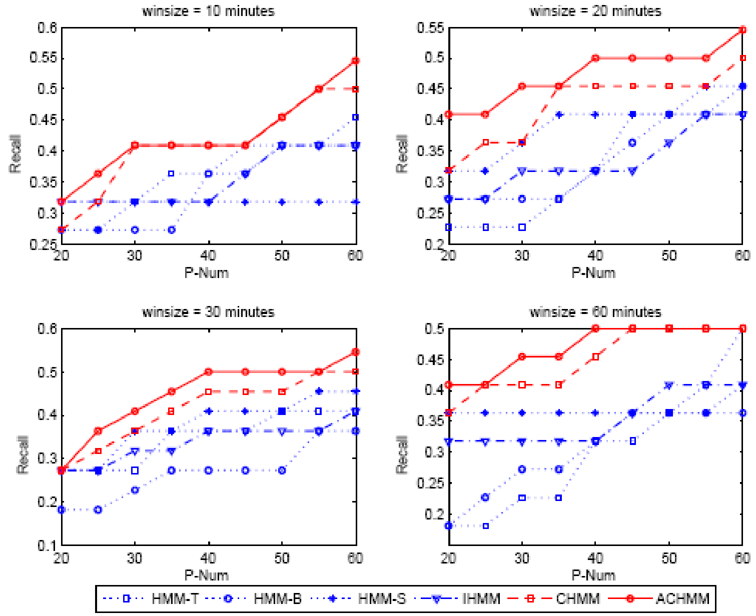


Figure 6: Recall of Six Models

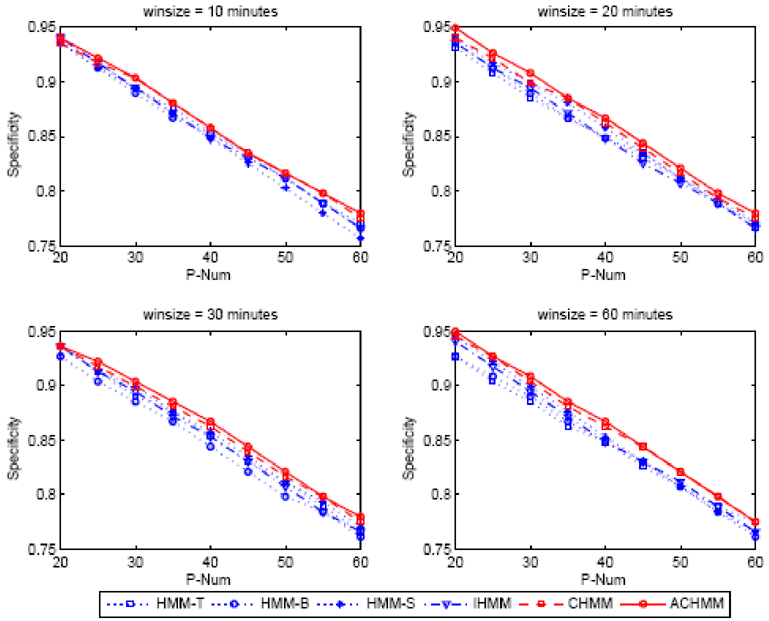


Figure 7: Specificity of Six Models

• Business Performance

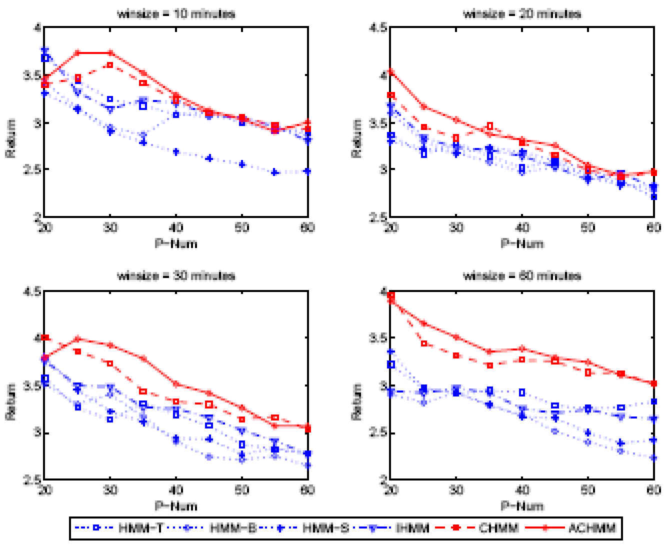


Fig. 9. Return of Six Models

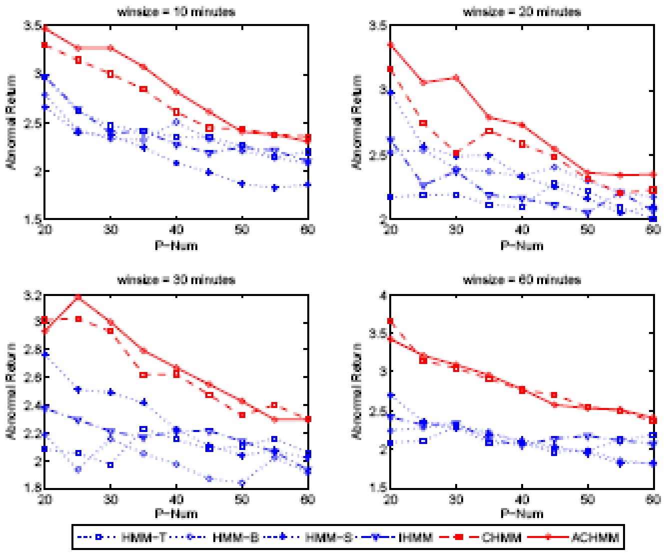


Fig. 10. Abnormal Return of Six Models

Example 2:
Coupled Hidden Markov Model-based Financial Crisis Analysis

- Deep Modeling Complex Couplings within Financial Markets
- Financial Crisis Forecasting via Coupled Market State Analysis
- Coupled Behavior Analysis with Applications

Challenges

- Couplings within/between financial markets
- Couplings within/between financial variables
- Heterogeneity between markets, between financial variables

Modeling within/between-market couplings

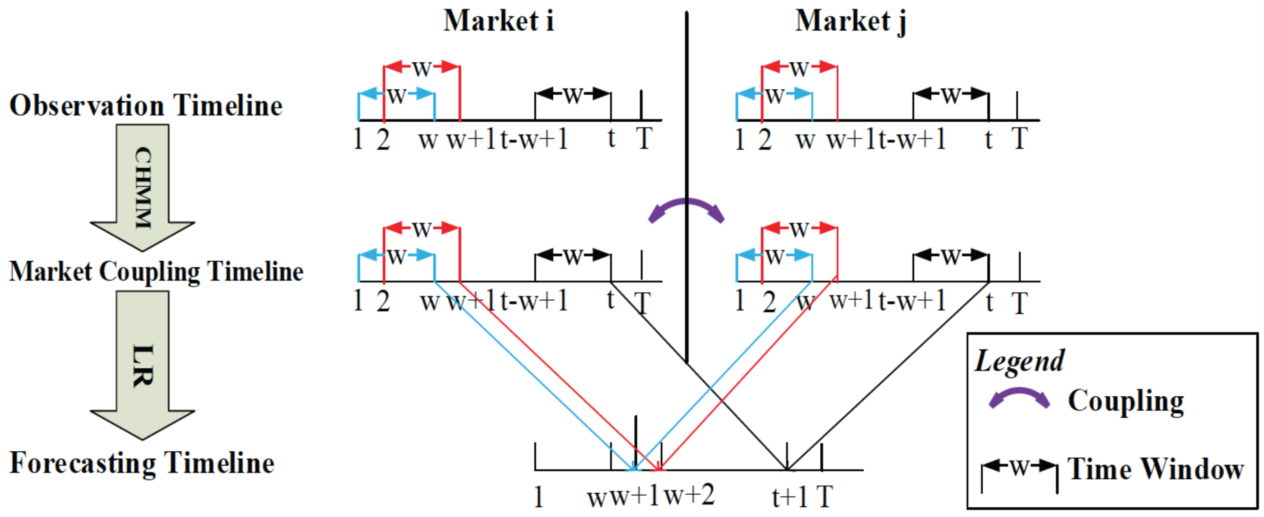


Fig. 3: Forecasting Process

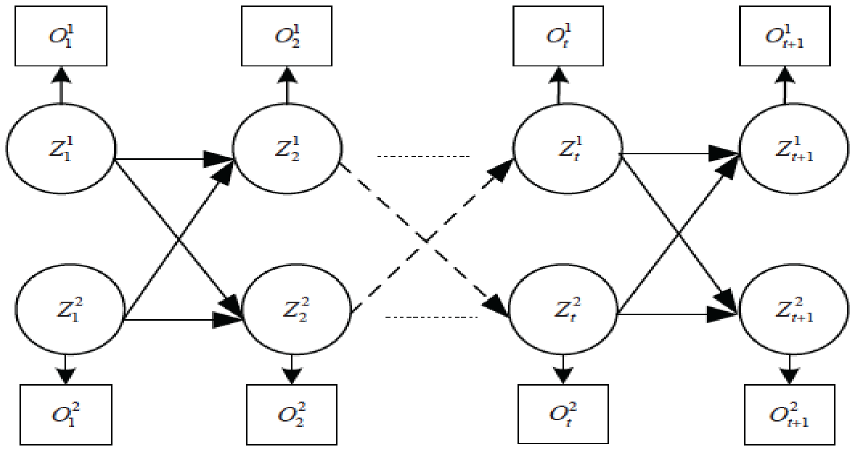
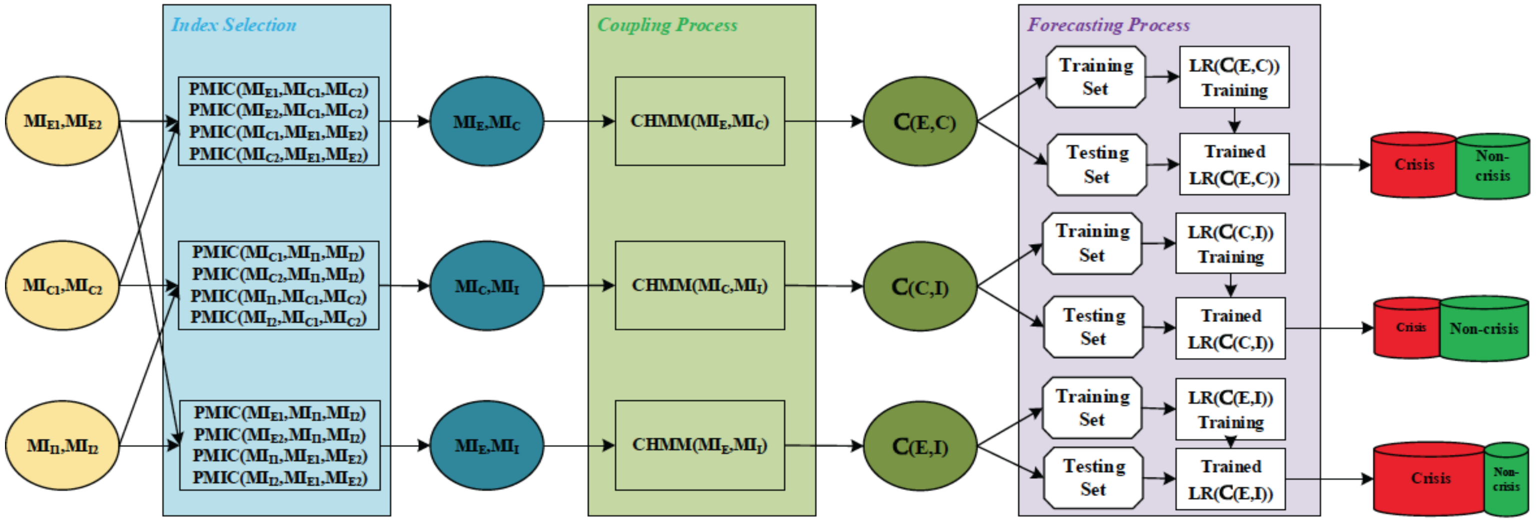


Fig. 1: A CHMM with Two Chains

- Temporal/periodical transition
- State transition within a market
- Coupling between markets
- CHMM for both transitions/influence within and between sequences

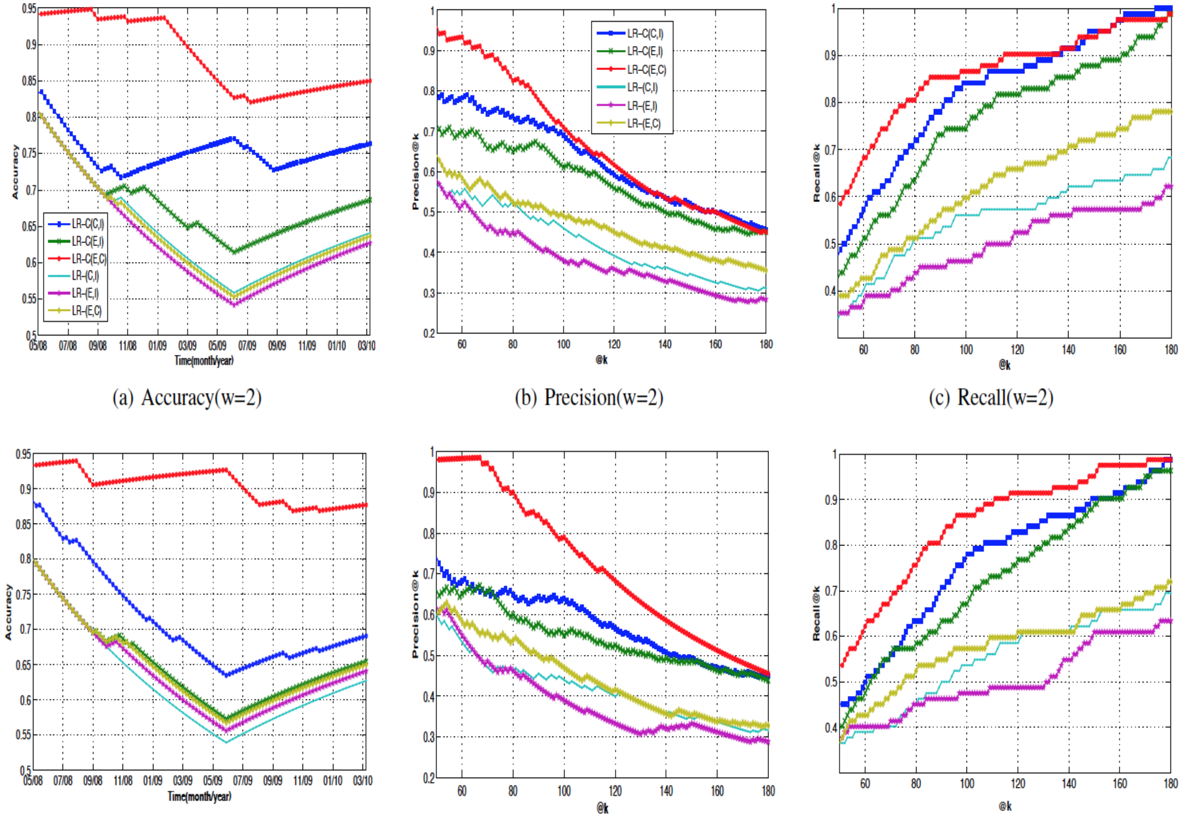
Modeling within/between-market couplings



- CHMM-LR:
  - (1) couplings between equity market and commodity market ($\mathcal{C}(E,C)$);
  - (2) couplings between equity market and interest market ($\mathcal{C}(E,I)$);
  - (3) couplings between commodity market and interest market ($\mathcal{C}(C,I)$).

- Select financial variables
- Modeling their within/between sequence couplings
- Forecasting

Case study: financial crisis



(a) Accuracy(w=2) (b) Precision(w=2) (c) Recall(w=2)

(d) Accuracy(w=3) (e) Precision(w=3) (f) Recall(w=3)

Fig. 7: Technical Performance of Various Approaches

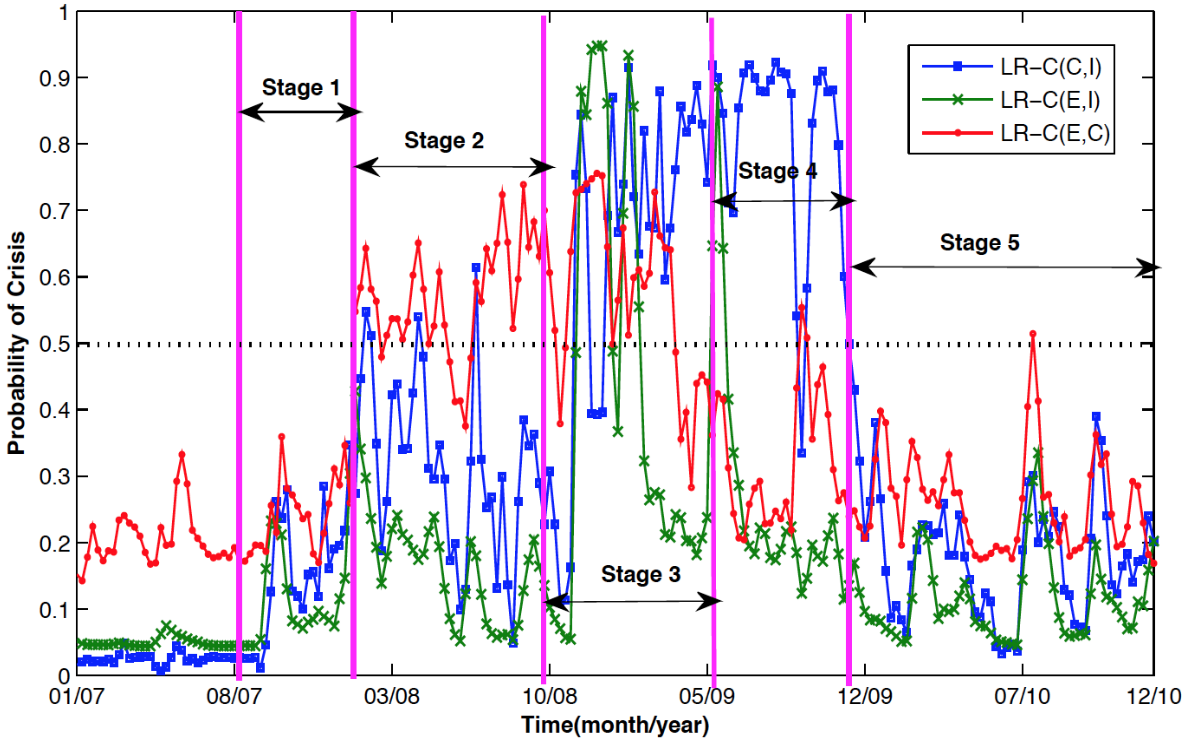


Fig. 8: Market Couplings Behavior during 2008 Financial Crisis ($w = 2$)

TABLE II: Selected Indicators

Pairwise Coupling	Market Indicator
$\mathbb{C}(E, C)$	E: DJIA /C:WTI Oil Price
$\mathbb{C}(C, I)$	C: Gold Price/C:TED Spread
$\mathbb{C}(E, I)$	E: DJIA /I:BAA Spread

Example 3:
Copula-based Cross-market Dependence Structure Modeling

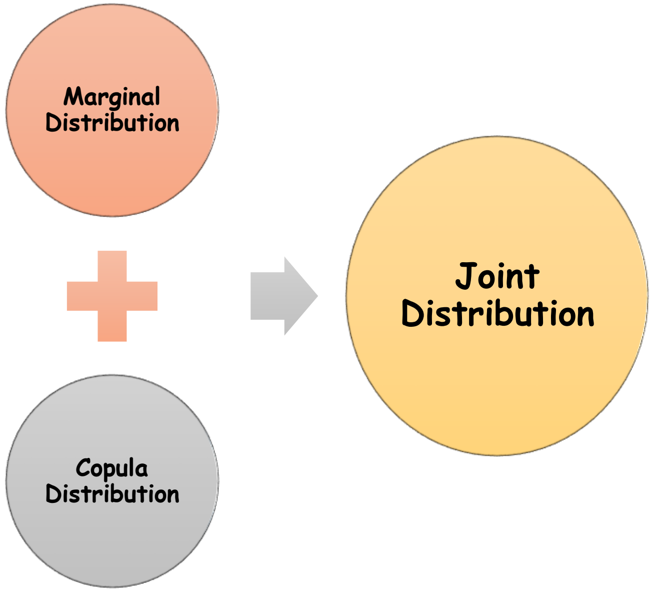
- Copula-Based High Dimensional Cross-Market Dependence Modeling
- Modeling Asymmetry and Tail Dependence among Multiple Variables by Using Partial Regular Vine
- Model the Complex Dependence Structures of Financial Variables by Using Canonical Vine
- Vine Copula-based Asymmetry and Tail Dependence Modeling

Challenges

- Multiple heterogeneous financial variables
- Stylized fact: fat tail and asymmetric correlations
- Dependence strength and structure

Copula-based dependence modeling

- Modeling joint distribution between a group of random variables



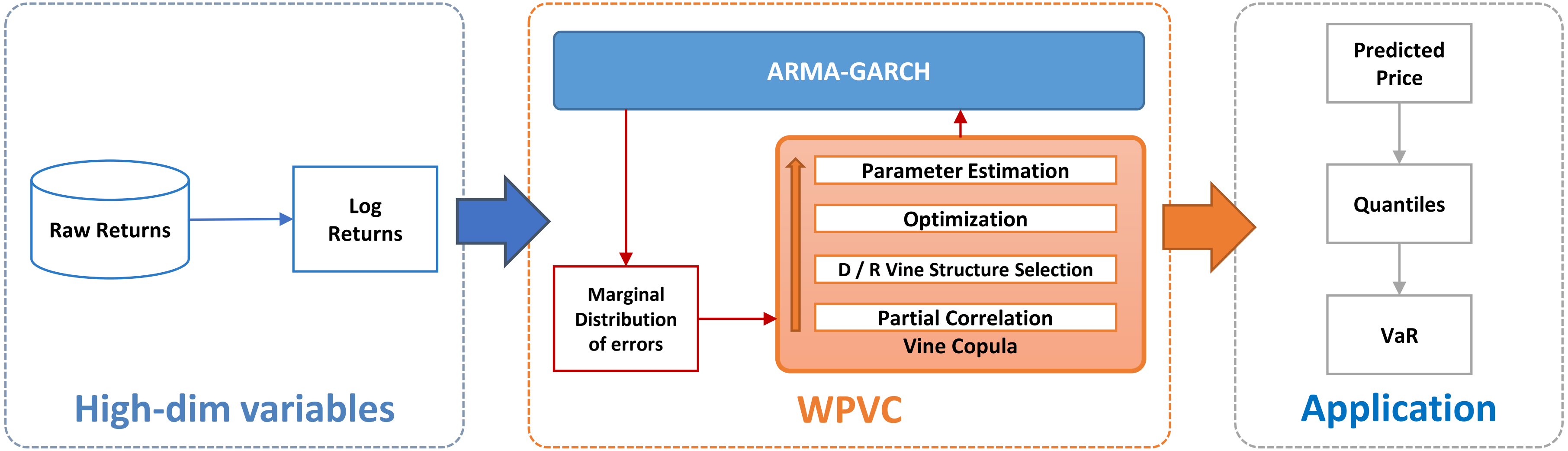
$$F_1(x_1, x_2, \ldots, x_n) = C(F_1(x_1), F_2(x_2), \ldots, F_n(x_n))$$

$$C(u_1, u_2, \ldots, u_n) = F(F_1^{-1}(u_1), F_2^{-1}(u_2), \ldots, F_n^{-1}(u_n))$$

$$f(x_1, x_2, \ldots, x_n) = c(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) \prod_{i=1} f_i(x_i)$$

Partial vine for structural dependence

- Weighted partial vine copula (WPVC)



- Partial D vine tree structure for asymmetric dependence in tail risk
- Bivariate copula with different types of tail dependencies
- Truncation with conditional independence (vs. correlations) for high-dimensional

Partial correlation

- Partial D vine structure

$$\rho_{1,2;3,\ldots,n} = \frac{\rho_{1,2;3,\ldots,n-1} - \rho_{1,n;3,\ldots,n-1} \cdot \rho_{2,n;3,\ldots,n-1}}{\sqrt{1-\rho^2_{1,n;3,\ldots,n-1}} \cdot \sqrt{1-\rho^2_{2,n;3,\ldots,n-1}}}$$

- Lower and upper tail dependence coefficients

$$\begin{aligned}
\lambda_L &= \lim_{u\to 0} Pr\{U_1 \le u, \ldots, U_n \le u \mid U_n \le u\} \\
&= \lim_{u\to 0} \frac{C(u, \ldots, u)}{u} \\
\lambda_U &= \lim_{u\to 0} Pr\{U_1 > 1-u, \ldots, U_n > 1-u \mid U_n > 1-u\} \\
&= \lim_{u\to 0} \frac{\overline{C}(1-u, \ldots, 1-u)}{u}
\end{aligned}$$

- *0*
- $\in (0, 1]$

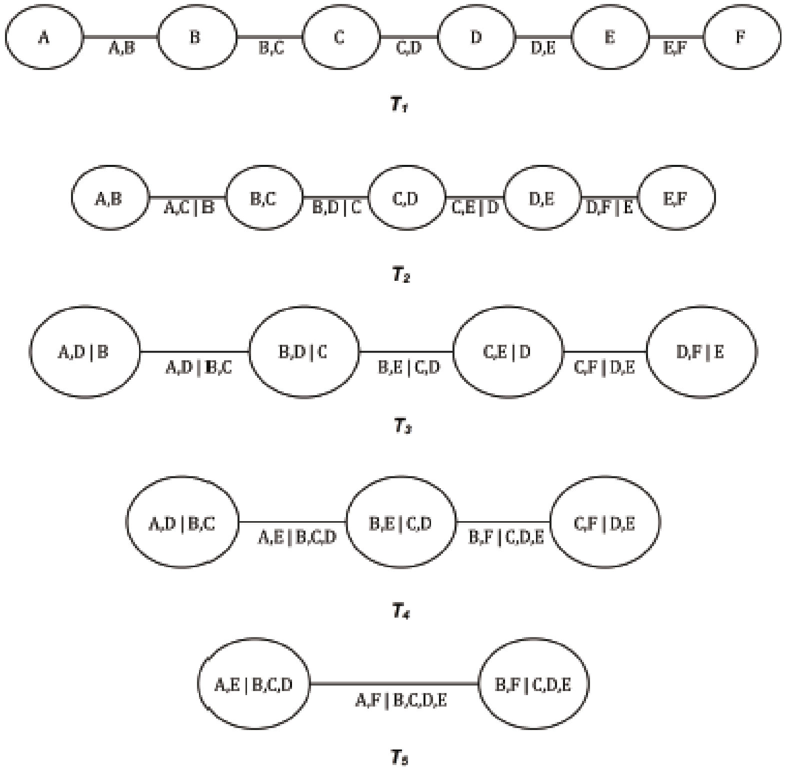
Partial D vine tree construction

Weighted partial D vine tree construction

- 6 variables, 20 partial correlations
- The smallest PC as the edge of T5: {A,F;B,C,D,E}, conditioned set {A,F} and conditioning set {B,C,D,E}
- Nodes in T5:
  - Constraint sets {A,B,C,D,E} and {F,B,C,D,E}
  - Find the smallest PC for each constraint set and treat them as nodes, e.g. {A,E;B,C,D} and {B,F;C,D,E}
- T4, T3
- Best D vine:

argmax(-*ln*(*D*))

$$D = \prod_{i,j} (1 - W_i \rho^2_{i,j;d(i,j)})$$



$$W(h) = \begin{cases} 0.5 \times \frac{e^{-m_0(k-h)}}{\sum_{i=1}^{k} e^{-m_0(k-i)}}, & h \in [1, k]; \\ 0.5 \times \frac{e^{-m_0(h-k)}}{\sum_{i=k+1}^{N-1} e^{-m_0(i-k)}}, & h \in (k, N-1]. \end{cases}$$

Parameter estimation

- Maximum Log-Likelihood estimation to estimate the parameters of copula constructed w.r.t. vine structures

$$L(\xi : x) = \sum_{j=1}^{n} \left\{ \sum_{i=1}^{p} \ln f_i\left(x_{i,j}; \phi_i\right) + \ln c\left(F_1(x_1, n), F_1(x_2, n) \cdots, F_p\left(x_p, n\right); \theta\right) \right\}$$

$$\xi = (\phi_1, \dots \phi_p, \theta)$$

Estimate parameters for marginal distributions:

$$L_m(\phi : x) = \sum_{i=1}^{p} \sum_{j=1}^{n} ln f_i(x_{i,j}; \phi_i) \qquad \hat{\phi} = \underset{\phi}{\operatorname{argmax}}\, L_m(\phi : x)$$

Estimate parameter in copula:

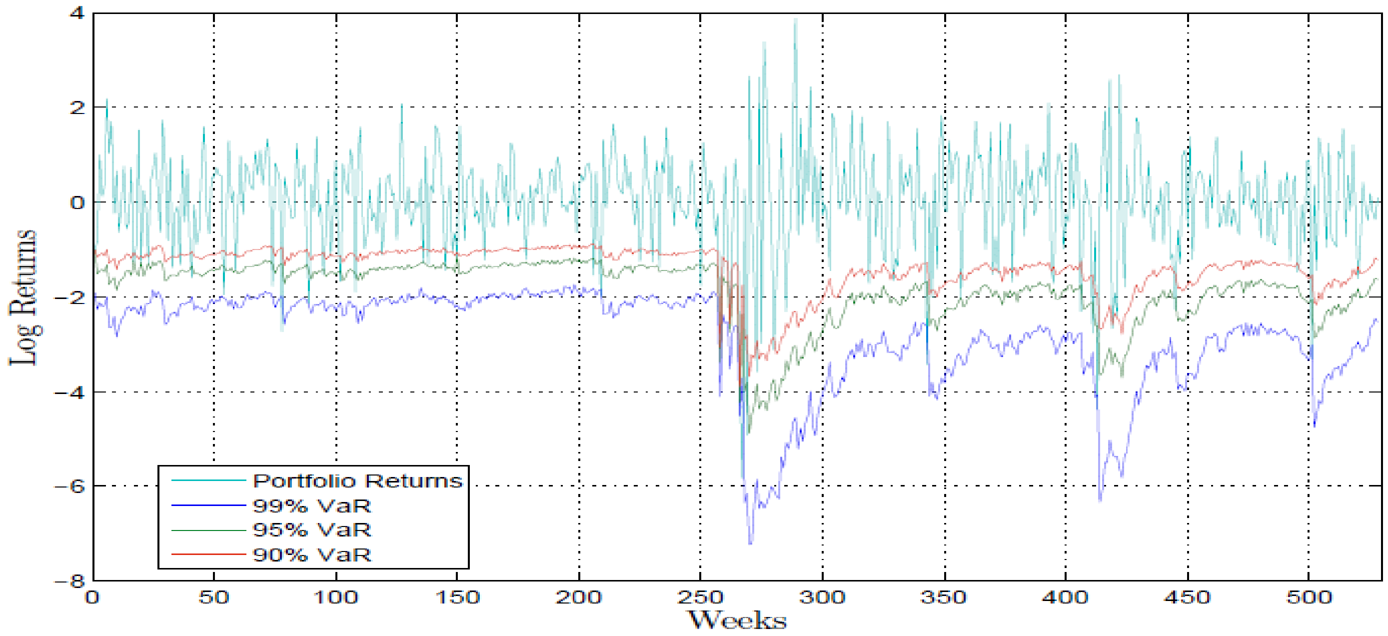
$$L_c(\theta; u, \phi) = \sum_{i=1}^{p} ln(c(F_1(x_1, n), \dots, F_p(x_p, n); \theta)) \qquad \hat{\theta} = \underset{\theta}{\operatorname{argmax}}\, L_c(\theta; u, \phi)$$

Case study

- Backtesting VaR – Log-likelihood ratio

	$1-\alpha$	POF^1	${LR_{UC}}^2$	${LR_{IC}}^2$	${LR_{CC}}^2$
$WPVC_{0.05}$	99%	5 1.08%	0.0324 (0.857)	2.315 (0.314)	2.347 (0.143)
	95%	26 5.64%	0.382 (0.536)	0.188 (0.868)	0.570 (0.752)
	90%	52 11.50%	1.100 (0.294)	1.582 (0.254)	2.683 (0.261)
D_STD	99%	9 1.95%	2.186 (0.139)	2.221 (0.136)	4.408 (0.110)
	95%	27 5.86%	0.451 (0.730)	0.133 (0.916)	0.584 (0.618)
	90%	57 12.36%	1.363 (0.547)	3.533 (0.176)	4.896 (0.086)
D_Ken	99%	10 2.17%	3.376 (0.066)	1.843 (0.175)	5.218 (0.074)
	95%	27 5.86%	0.451 (0.730)	0.133 (0.916)	0.584 (0.618)
	90%	57 12.36%	1.363 (0.547)	3.533 (0.033)	4.896 (0.086)
$Cvine$	99%	11 2.39%	4.770 (0.029)	1.439 (0.230)	6.209 (0.045)
	95%	29 6.29%	0.662 (0.628)	0.042 (0.838)	0.704 (0.554)
	90%	59 12.80%	1.782 (0.326)	4.469 (0.035)	6.251 (0.025)
DCC	99%	103 22.34%	466.082 (0.000)	5.449 (0.021)	471.533 (0.000)
	95%	133 28.85%	276.570 (0.000)	15.257 (0.004)	291.827 (0.000)
	90%	59 32.97%	180.570 (0.000)	15.333 (0.004)	195.903 (0.000)

- VaR forecasting of portfolio return



- 25 indicators: 8 exch rates, 13 indices, 3 comdity, 1 comdty index
- In-sample: 5 years; out-of-sample: 10 years
- ARMA(1; 1)-GARCH(1; 1): stocks
- AR(1)-GARCH(1; 1): exchange rate

Example 4:
Deep Neural Modeling of Cross-market Couplings

- Deep Modeling Complex Couplings within Financial Markets

Market couplings

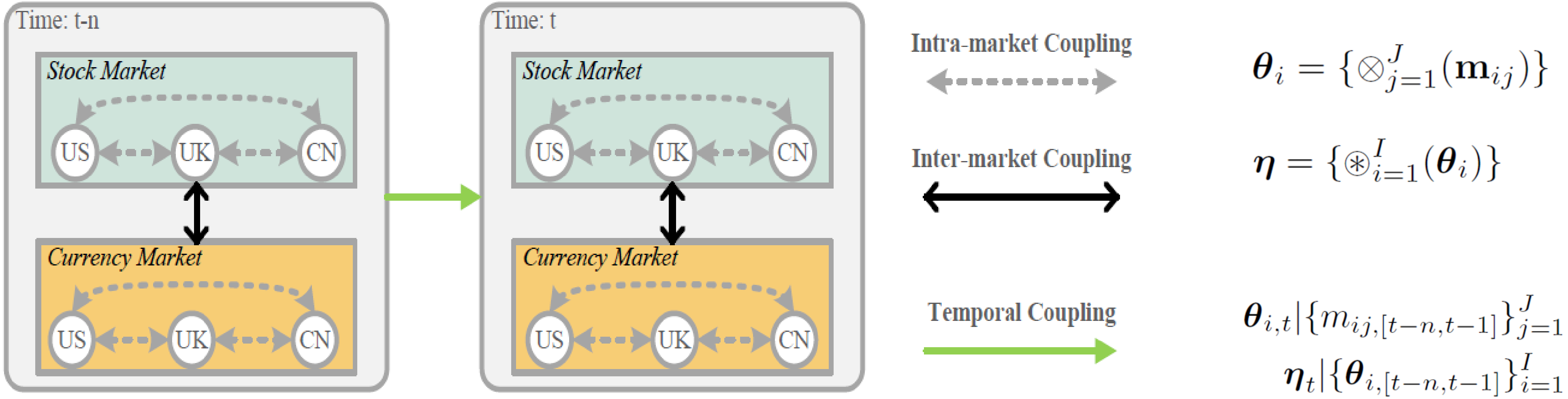


Figure 1: A demonstration of complex couplings between financial markets

- Observable variables: dependencies or correlations
- Deep/hidden variables: and their relations
- Temporal couplings

Two-layer cross-market coupling learning

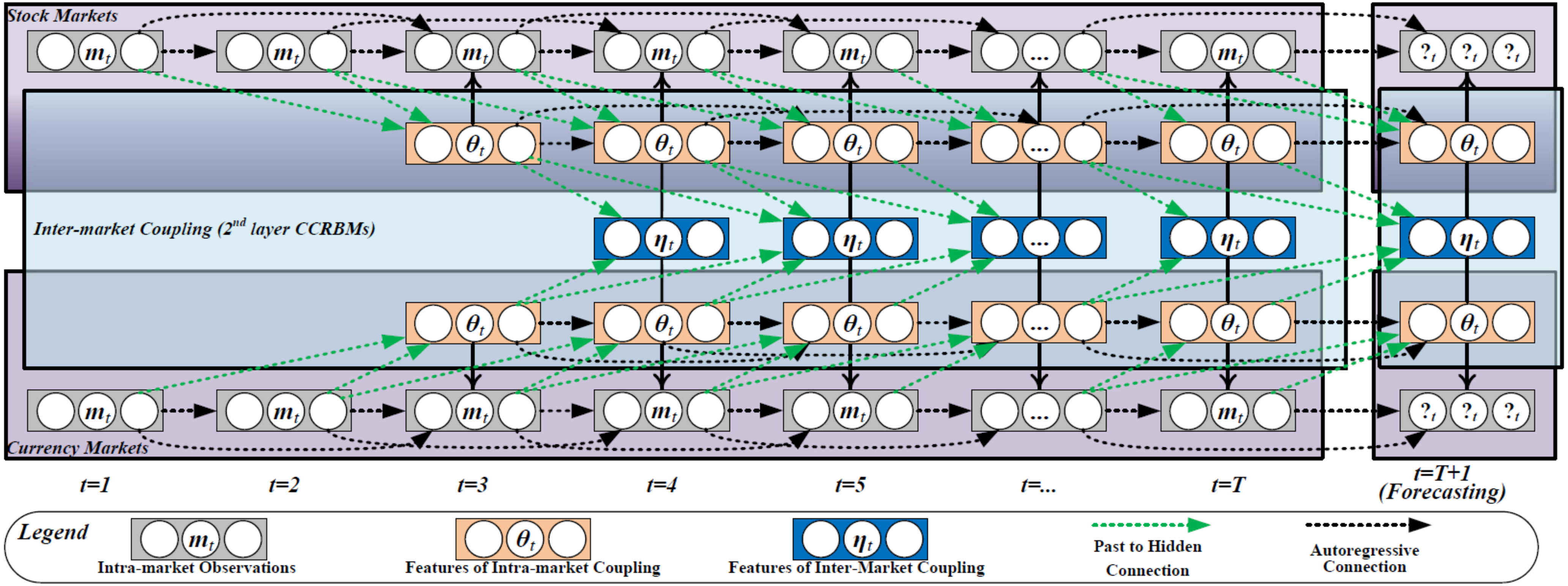
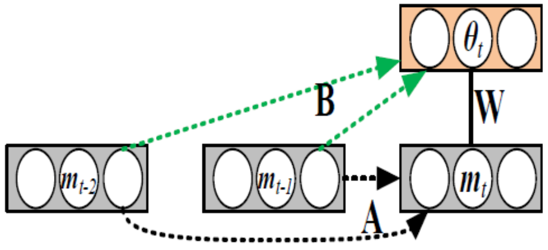


Figure 2: Modeling framework of CTDBN. Here, the demonstration shows two heterogeneous financial markets, stock and currency. The first-layer are CGRBMs to model the intra-maket couplings while CCRBMs are built on the first layer to model inter-market couplings.

Intra/inter-market couplings



(a)

Conditional Gaussian Restricted Boltzmann Machines: CGRBM intra-market couplings

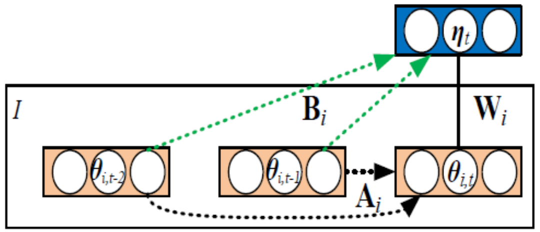
$$P(\mathbf{v},\mathbf{h} \mid \mathbf{u}) = exp(-E(\mathbf{v},\mathbf{h},\mathbf{u}))/Z$$

$$E(\mathbf{v},\mathbf{h},\mathbf{u}) =$$

$$-\frac{\mathbf{v^T W h}}{\sigma} - \mathbf{u^T A v} - \mathbf{u^T B h} + \frac{(\mathbf{v}-\mathbf{a})^{\mathbf{T}}(\mathbf{v}-\mathbf{a})}{2\sigma^2} - \mathbf{b^T h}$$

$$P(h_f = 1 \mid \mathbf{v},\mathbf{u}) = s(b_f + \mathbf{u^T B}_{:,f} + \mathbf{v^T W}_{:,f}/\sigma)$$

$$P(v_d \mid \mathbf{v},\mathbf{u}) = \mathcal{N}(a_d + \mathbf{u^T A}_{:,d} + \sigma \mathbf{W}_{d,:}\mathbf{h}, \sigma^2)$$



(b)

Figure 3: (a) A CGRBM to model intra-market coupling at time t; (b) A CCRBM to model inter-market coupling at time t

Coupled Conditional Restricted Boltzmann Machines: CCRBM inter-market couplings

$$E(\{\boldsymbol{\theta}_{i,t}\},\boldsymbol{\eta}_t,\{\boldsymbol{\theta}_{i,<t}\}) = -\mathbf{b}^T\boldsymbol{\eta}_t - \sum_{i=1}^{I}\mathbf{a}_i^T\boldsymbol{\theta}_{i,t} -$$

$$\sum_{i=1}^{I}\boldsymbol{\theta}_{i,t}^T\mathbf{W}_i\boldsymbol{\eta}_t - \sum_{i=1}^{I}\boldsymbol{\theta}_{i,<t}^T\mathbf{A}_i\boldsymbol{\theta}_{i,t} - \sum_{i=1}^{I}\boldsymbol{\theta}_{i,<t}^T\mathbf{B}_i\boldsymbol{\eta}_t$$

$$P(\theta_{ift} = 1 \mid \boldsymbol{\eta}_{ht},\{\boldsymbol{\theta}_{i,<t}\}) =$$

$$s(\mathbf{a}_{if} + \boldsymbol{\theta}_{i,<t}^T(\mathbf{A}_i)_{:,f} + (\mathbf{W}_i)_{f,:}\boldsymbol{\eta}_t)$$

$$\boldsymbol{\theta}_{i,<t} = [\boldsymbol{\theta}_{i,t-1},\boldsymbol{\theta}_{i,t-2},\ldots,\boldsymbol{\theta}_{i,t}$$

$$P(\eta_{ht} = 1 \mid \{\boldsymbol{\theta}_{i,t}\},\{\boldsymbol{\theta}_{i,<t}\}) =$$

$$s(\mathbf{b}_h + \sum_{i=1}^{I}\boldsymbol{\theta}_{i,t}^T(\mathbf{W}_i)_{:,h} + \sum_{i=1}^{I}\boldsymbol{\theta}_{i,<t}^T(\mathbf{B}_i)_{:,h})$$

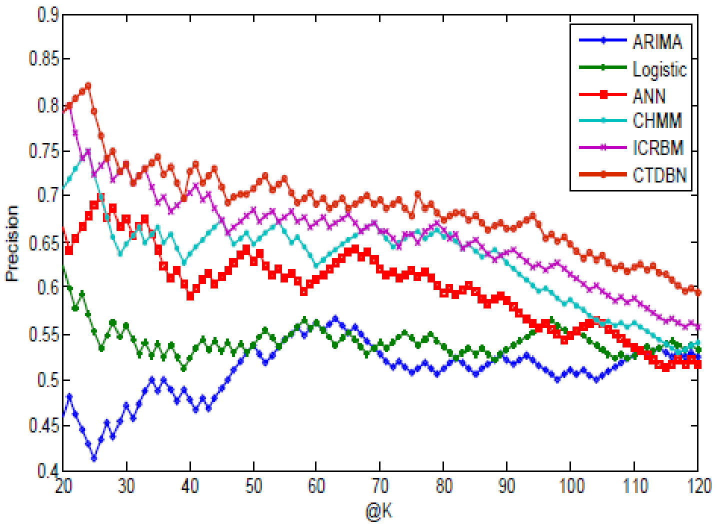
Return prediction

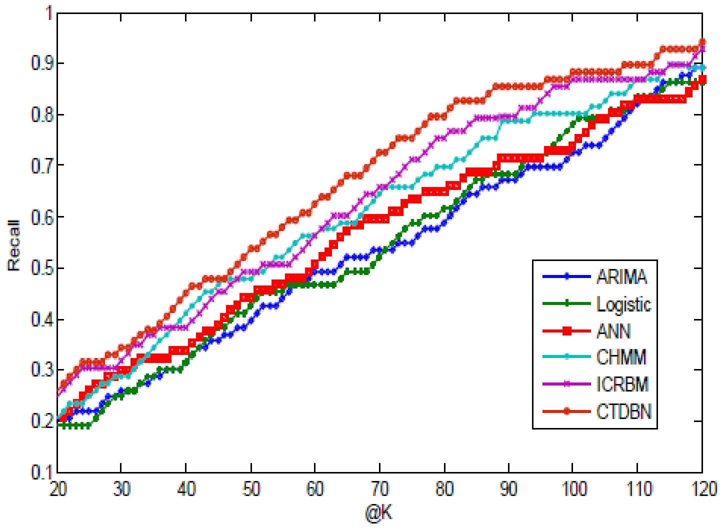
Table 2: Performance of comparative methods in US, China and India markets

Model	Accuracy						ARR					
	Stock			Currency			Stock			Currency		
	US	China	India	US	China	India	US	China	India	US	China	India
ARIMA	0.5357	0.5071	0.5029	0.5471	0.5353	0.5214	-0.1356	0.0415	-0.0675	0.1479	-0.0116	0.0304
Logistic	0.5643	0.55	0.5196	0.6	0.6059	0.5386	0.0226	0.0796	0.0558	0.0269	0.0428	0.0645
ANN	0.6	0.6	0.5752	0.6235	0.6059	0.5747	0.1217	0.1486	0.0788	0.1332	0.1244	0.1032
CHMM	0.6533	0.6214	0.5852	0.6471	0.6353	0.5709	0.1934	0.1426	0.1132	0.1645	0.1498	0.1555
CGRBM	0.6357	0.6235	0.5898	0.6565	0.64	0.5932	0.1568	0.1526	0.1410	0.1758	0.1456	0.1660
CTDBN	**0.6729**	**0.6324**	**0.6258**	**0.6734**	**0.6535**	**0.6152**	**0.2073**	**0.1682**	**0.2261**	**0.1926**	**0.1792**	**0.1972**

Table 1: Trading indexes

Country	Market	
	Stock Market	Currency Market
USA	^DJI	SDR/USD
Brazil	^BVSP	SDR/BRL
Russia	RTS.RS	SDR/RUB
India	^BSESN	SDR/INR
China	000001.SS	SDR/CNY





Example 5:
Coupling Macro-Meso-Micro Financial Factors for Stock Representation

- Coupling Macro-Sector-Micro Factors on Learning Stock Representation with Less Uncertainty, AAAI-21

Complex multi-macro factors

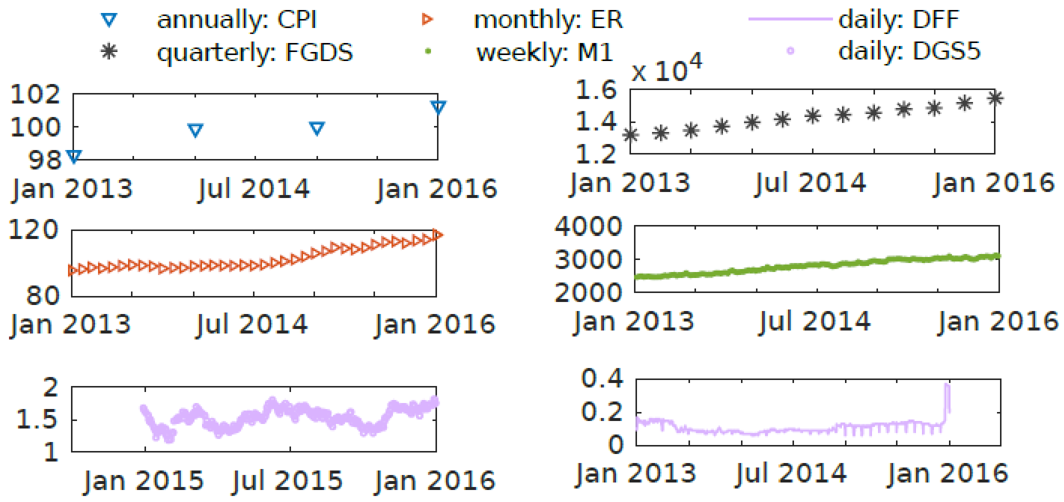


Figure 2: Some macro-factors to show their varied characteristics (i.e., time intervals, scales and distributions). The

Macro-factor context-based stock representation

$$\mathcal{L} = \frac{1}{2\gamma_1^2}\mathcal{L}_C + \frac{1}{2\gamma_2^2}\mathcal{L}_N + \log \gamma_1\gamma_2$$

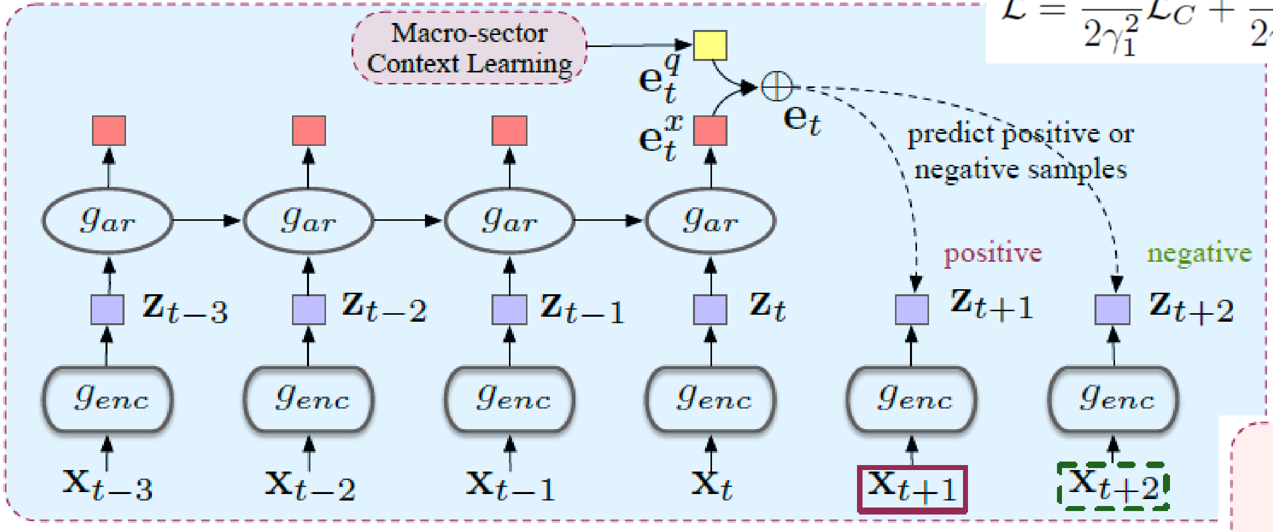


Figure 4: The framework of stock representation learning

$$C(\cdot) = \Phi_{\mathbf{R}}(\Phi^{-1}(F_0(q_0)), \ldots, \Phi^{-1}(F_m(q_m)))$$

$$\mathcal{L}_C = -\sum_{i=0}^{m}\left\{\log \Phi_{\mathbf{R}}(\mathbf{u}_0, \ldots, \mathbf{u}_m) + \sum_t \log \hat{f}_i(\tilde{q}_{i,t})\right\}$$

$$\boldsymbol{\alpha} = g_{gat}(\mathbf{R}) = Sigmoid(\mathbf{w}_R\mathbf{R} + \mathbf{b}_R)$$

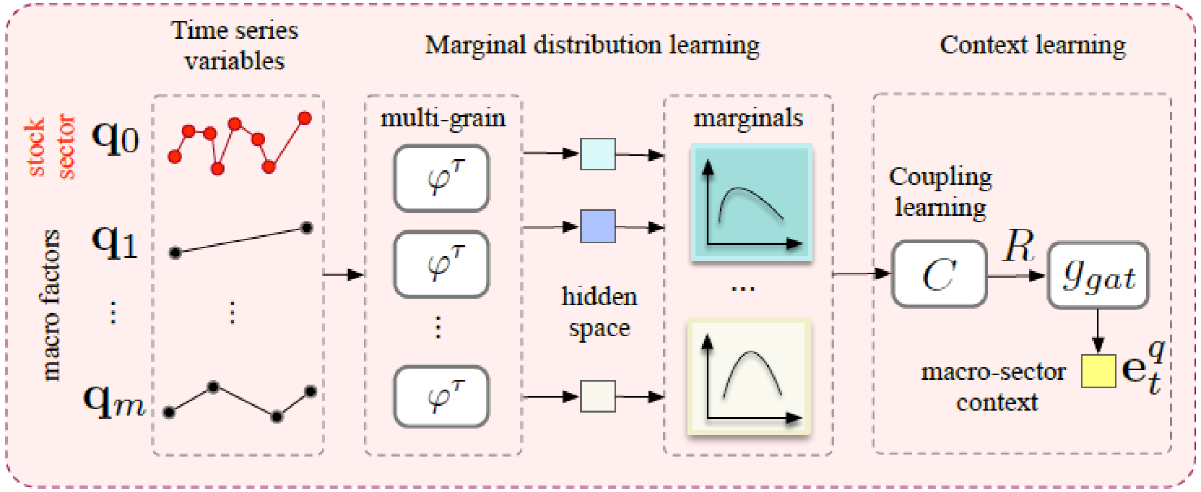


Figure 3: The framework of macro-sector context learning.

$$I(\mathbf{x}; \mathbf{e}) = \sum_{\mathbf{x},\mathbf{e}} p(\mathbf{x}, \mathbf{e}) \log \frac{p(\mathbf{x}|\mathbf{e})}{p(\mathbf{x})}$$

$$\mathbf{e}_t = \mathrm{MLP}([\mathbf{e}_t^q, \mathbf{e}_t^x])$$

$$f_k(\mathbf{x}_{t+k}, \mathbf{e}_t) \propto \frac{p(\mathbf{x}_{t+k}|\mathbf{e}_t)}{p(\mathbf{x}_{t+k})}$$

$$\mathcal{L}_N = -\mathbb{E}_{\mathbf{X}}\left[\log \frac{f_k(\mathbf{x}_{t+k}, \mathbf{e}_t)}{\sum_{x_j \in \mathbf{X}} f_k(\mathbf{x}_j, \mathbf{e}_t)}\right]$$

Method	ACL18		KDD17	
	Acc.	MCC	Acc.	MCC
StockNet	54.96	0.00165	51.93	0.0335
LSTM	53.18	0.0674	51.62	0.0183
ALSTM	54.90	0.1403	51.94	0.0261
Adv-ALSTM	57.20	0.1483	53.05	0.0523
CPC	58.14	0.1631	54.47	0.0746
Co-CPC	**58.90**	**0.1771**	**58.81**	**0.1643**
StockNet	58.23	0.0808	-	-
LSTM	56.82	0.1375	-	-
CPC	59.11	0.1817	-	-
Co-CPC	**61.62**	**0.2316**	-	-

Table 1: Performance comparison on two datasets.

Method	ACL18		KDD17	
	Acc.	MCC	Acc.	MCC
CPC	59.11	0.1817	54.47	0.0746
Co-CPC(monthly)	59.54	0.1892	56.94	0.1201
Co-CPC(weekly)	59.76	0.1960	57.02	0.1221
Co-CPC(daily)	60.03	0.2006	56.63	0.1142

Table 2: Performance comparison when consider macro-factors with various time intervals. The results of ACL18 dataset here are based on both prices and tweets features.

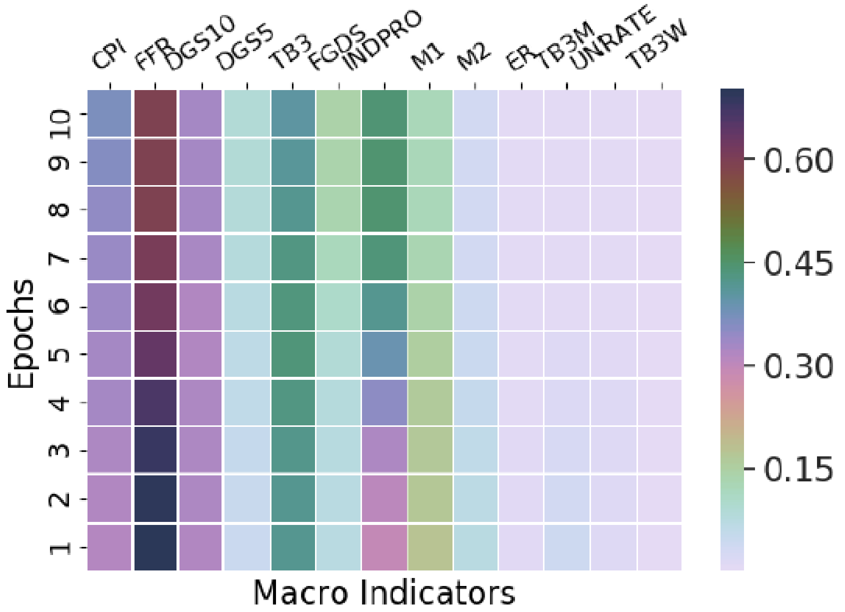
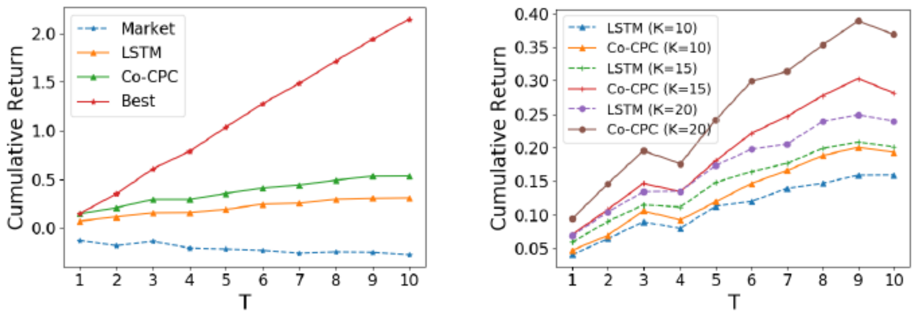


Figure 5: The impact degree of macro indicators.



(a) 1-th strategy (b) 2-th strategy

Figure 6: Cumulative return simulation on two strategies.

Concluding remarks

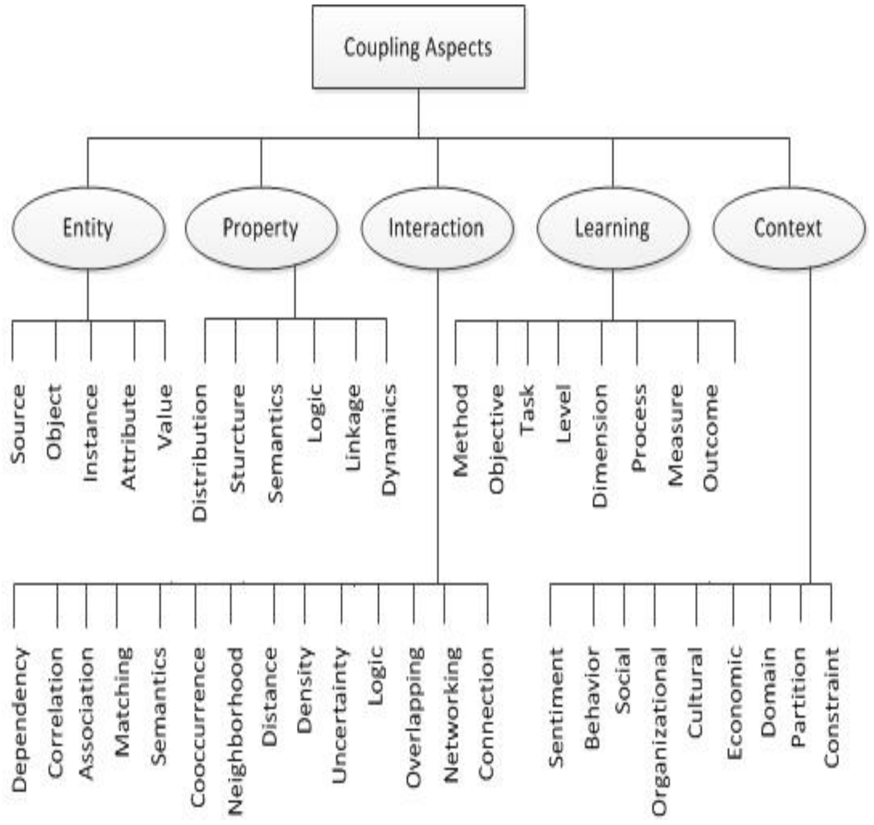
Opportunities

- AI-driven Strategic Planning and Development
  - Strategic planning and development
- AI-driven disaster management
  - Understanding and managing certainty, black swan/grey rhino events, and changes in economic-financial systems
- AI-enabled Economic-Financial Innovations

- Beyond AI and Finance
  - Neuropsychological foundation for AIDS and EcoFin
  - Social and ethical issues in AIDS-driven EcoFin
  - Geopolitical and geocultural influence
  - The economics of AIDS for economy and finance

Specifically, complex couplings in finance

- Macro/micro-variables across markets
- Structured/unstructured variables
- Observable and deep factors
- Within/between-variable couplings
- Couplings: dependence, correlation, hidden relations, etc.
- Nonstationary, heterogeneous, multiscale, stylistic, …



Coupling Learning of Complex Interactions

Thank you very much

More information

www.datasciences.org

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