

Brij Disa Centre for Data Science & Artificial Intelligence



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EVOLUTION OF HIGH FREQUENCY TRADING IN INDIA AND THE IMPACT OF REGULATIONS ON HFT ACTIVITY



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Prof. Banerjee's research interests are in the microstructure of financial markets, derivative markets, and financial networks. His research focuses on the role of algorithmic and high-frequency traders in regard to the provisioning of liquidity and pricing information.



Prince

Prince is a Pre-Doctoral Research Associate at IIM Ahmedabad. His research interest includes market-microstructure, impact of technology on financial markets. He is a BS-MS graduate from IISER Kolkata.



More than five decades ago, Fisher Black offered the idea of a fully automated stock exchange over the traditional one. With the advent of technology, it appears likely that a stock exchange may be implemented as a network of computers, resulting in drastically lower trading costs without increasing stock price volatility or creating an unequal playing field for small or large investors. We are reasonably close to a trading world where Exchange servers have essentially taken the position of trading floors. These new venues include dark pools, crossover networks, and centralized limit-order marketplaces. Most of the services that brokers, dealers, and experts provide have been incorporated into super-fast computer algorithms. All asset classes and securities trading have moved entirely to the electronic market or are migrating.

The type of computerized trading that has perhaps attracted the highest attention over the last decade is high-frequency trading (HFT). HFT is a type of algorithmic trading that uses intraday financial data and electronic trading instruments. It is characterized by extremely high trade execution speeds, high turnover rates, low inventory, and high order-to-trade ratios. Although there is no official definition of HFT, it typically refers to computer programs generating trading signals and submitting orders to the exchanges without any real-time human intervention, typically used by proprietary traders. Their collective trade participation rate is usually a few deciles (SEC 2010). These systems often work for privately held companies rather than the wealthy sell-side banks. They must keep their investments small and brief to avoid having too much money invested in margin accounts. They avoid holding positions overnight and engage in intraday trading.

Based on different underlying philosophies, HFT traders employ various strategies such as order flow prediction, VWAP¹ or TWAP², arbitrage, market making, etc. Our work primarily focuses on the evolution of high-frequency trading in India in the last decade and the impact of regulation on HFT's market-making strategy. Every market-maker functions by providing buy and sell quotes for certain securities. As soon as an order is received from a buyer/seller matching the quotes of the market maker, trades are executed. Consequently, these traders provide continuous liquidity in the market.

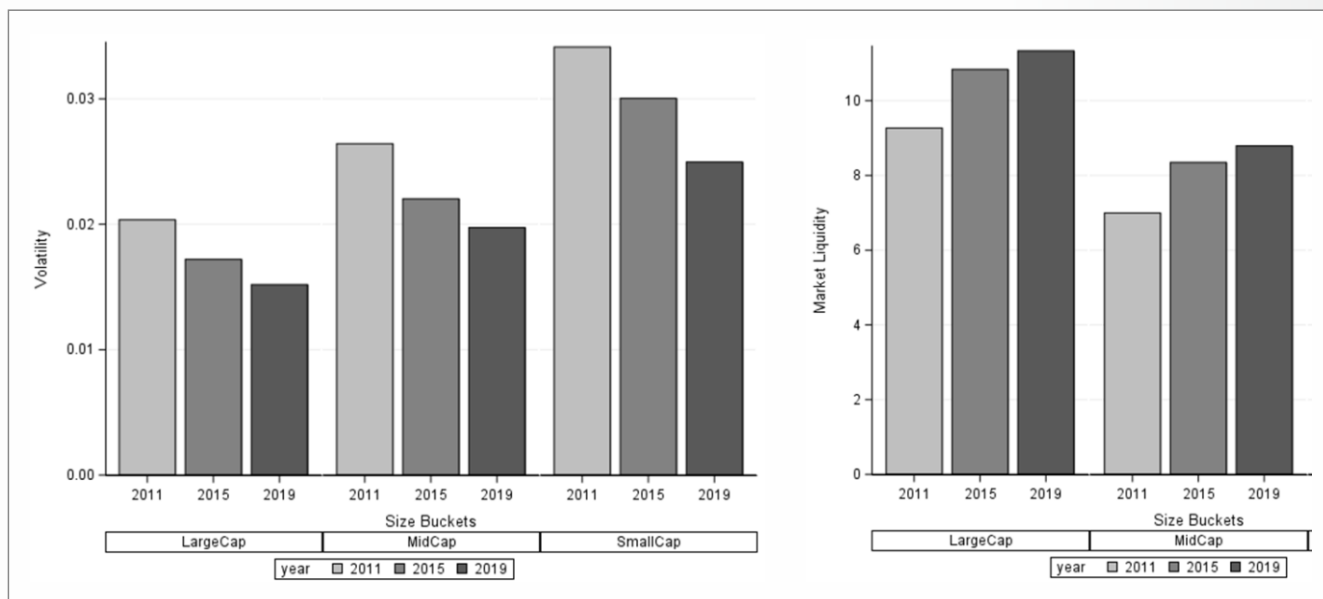
NSE was founded in 1992 and implemented electronic screen-based trading in 1994 and online trading in 2000. NSE has exceeded the incumbent BSE³ in terms of market share and dominates both equity as well as derivatives segments. NSE presently lists almost 1900 firms. It accounts for 91% of India's equities market volume, and its spot market turnover in 2019-20 was 900 trillion INR (or 12.8 trillion USD). NSE is a limit-order-driven market with strict price-time priority with no market-maker or specialist, and it operates from 9:15 AM IST to 3:30 PM IST. The provisioning of Direct Market Access (DMA) in 2008 was the first step toward algorithmic trading in India. NSE offered co-location facilities in 2010, allowing traders to deploy servers on-site. In November 2012, the charge for using co-location facilities was cut in half, which boosted algorithmic trading in the coming years. Since then, algorithmic and high-frequency trading has grown in India. We analyze the first quarter of 2011, 2015, and 2019, representing the inception, expansion, and stabilization phases of HFT and algorithmic trading in the Indian market.

¹ Volume-Weighted Average Price

² Time-Weighted Average Price

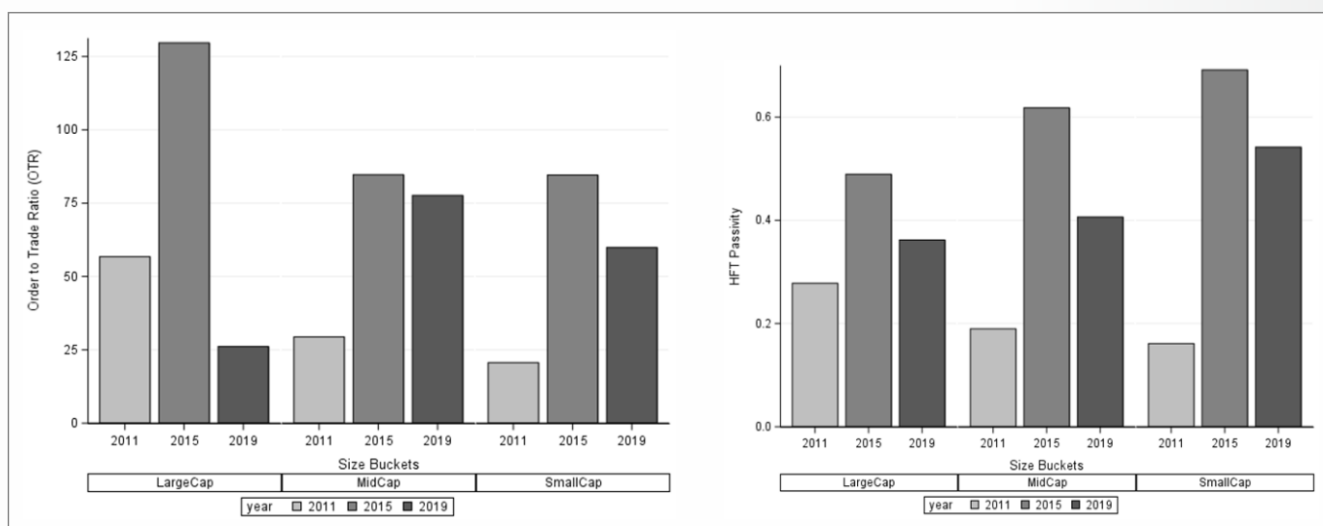
³ Bombay Stock Exchange

Existing Literature implies that as technology advances, HFT participation should boost market quality parameters, primarily liquidity and volatility. We observe the same for Indian markets too. Our analysis shows that over time liquidity has increased while volatility has decreased, eventually improving market quality. To measure HFT activity, we employ trade participation and passivity. HFT trading can be active or passive. As active trade participants, HFTs can act as opportunistic liquidity takers in contrast to liquidity providers during passive trading. Passive market-making decreases spread by raising competition and queue priority (Hasbrouck, 2018; J. Brogaard & Garriott, 2019). HFTs play both roles depending on their strategies' profitability. More HFTs as passive participants or market-makers are preferable from a market perspective, eventually boosting market liquidity.



We observe that HFT participation in NSE has grown over time. In 2011, it accounted for less than 1% of overall trading volume, while it grew to 6.3% in 2015 and 14.8% in 2019⁴. HFT participation is much higher for large-cap or mid-cap stocks compared to small-cap stocks, which is intuitive and is primarily due to the higher liquidity of these stocks. For the same period, HFT passivity rose from 19% in 2011 to 63% in 2015, then fell to 47% in 2019. In 2011, most HFTs acted as liquidity takers to discover profitable trading opportunities exploiting latency. During 2015, over two-thirds of HFT trading volume was contributed by them acting as liquidity providers a.k.a market-makers. In 2019, despite increased HFT participation in trades, a significant share acted as liquidity takers. HFT passivity was lower for larger-sized firms during 2015 and 2019. Also, from 2015 to 2019, we find that HFT passivity decreased by more than 10% across all size categories.

⁴ For the overall market



The market-making HFTs use a few channels to remain profitable such as exchange arbitrage, volume discount, frequent order modifications, order cancellation, and fleeting orders. HFTs, while acting as market makers, need to update their quotes frequently. So, only a fraction of the original orders gets executed. This results in a very high order-to-trade ratio (OTR). HFTs are best viewed as a brand-new intermediary category with the potential to enhance or degrade market quality. This crucial issue is debated in the media, among regulators, and the business world. To prevent market manipulation and protect other investors' ability to buy and sell securities, traders who make decisions based on short-term price trends and disparities must be subject to effective regulation. In 2018, the market regulator SEBI imposed a penalty on high OTR (order-to-trade ratio) that acts as a regulatory intervention for HFT market-making activity. In fig 5, we observe that the order-to-trade ratio (OTR) resembles the same pattern over time which we observed in the case of HFT passivity, where it increased from 2011 to 2015, and there's a

significant drop in 2019 from 2015. We find a linear relationship between passivity and the order-to-trade(OTR) ratio. We observe that post the 2018 regulation, though HFT participation increased across stocks, HFT passivity or market-making activity reduced. This reduction in HFT passivity may be detrimental to other investors (retail) in terms of reduced market liquidity. With a penalty on high OTR, the HFTs are likely to shift more towards opportunistic trading strategies that may negatively impact the market.

Our research explores the function of high-frequency traders in modern financial markets. With the technical advancement, the market share of high-frequency traders will increase, but their growth as market-makers depends on financial regulations. Sanctions on new trader groups for high OTR may prevent market manipulation, but it may affect HFT market-making and leading them to pursue opportunistic trading. This, in effect, may harm the same other non-sophisticated market participants. The findings impact academics and policymakers. Market regulators must consider the possible repercussions of HFT-related regulations.

APPLYING OPERATIONS RESEARCH IN OFFICE SPACE PLANNING IN POST-COVID WORLD



Abhik

Abhik is currently leading the Optimization & Simulation team in the Advanced Analytics Office at Western Digital, India. He has previously worked with Bayer, FICO, Intel where he applied mathematical optimization to solve challenging problems in different industries.



Planning office space has become an interesting problem in the post-COVID world. With the emergence of hybrid mode of working, companies have been forced to revisit their investment strategy in office space which constitutes a significant portion of their capital expenditure. How can we apply Operations Research to solve this problem?

Say a company has one or multiple offices in a city. During the 2 years of pandemic, the company has increased its strength by 50% in the city but did not expand its office space as most people were working remotely. Now that many employees have resumed working from office, the company needs to solve the following puzzles:

- 1) How to fit the additional 50% employees in the same space? Every employee would not be coming to office daily. Different teams would have preferences, around which days of the week they want to visit office/weekly frequency/number of employees who would be visiting office.
- 2) How to allocate seats to employees? Seats are no longer fixed – employees would not have dedicated cubicles anymore but could be assigned different seats on different days.

We propose an optimization model based on **Mixed Integer Linear Programming**, which determines:

- Number of people from each team who can visit office during each day of the planning horizon
- Area in the office that each team would occupy (Area could be floor-wing combination) during each day of the planning horizon

The model would be run in the last week of each month (planning horizon: next month) and would provide the output for each day of next month. Subsequently it would be run within the planning horizon if there are major changes in the input.

Note: Some rules can be customized according to the needs of the organization, they are marked with **

What objectives would the model meet?

- Minimize the deviation between input plan and output plan - within a day, across days of the week, across weeks of the month.
- Proportionally distribute seats across teams: Example: if capacity = 4000, and on a given day, 2 teams want to visit the office with seat requirement of 2500 and 3000, then allocate 1818 and 2182 seats respectively.
- Minimize number of wings shared across teams
- Maximize total occupancy i.e. use all available seats unless seat requirement is less than capacity Example: During Diwali/Christmas/New year, the allocation would be done so that only some floors/wings would be occupied. This would save electricity cost, housekeeping cost etc. for the unoccupied floors/wings.

What constraints would the model follow?

- 1) Do not exceed capacity of a floor-wing
- 2) To ensure members of the same team are seated as close as possible for ease of working, the model would try to fit members of the same team:
 - In the same wing

- Else in different wings of the same floor (assuming two wings in the same floor are equidistant)
 - Else in different but consecutive floors (to avoid crowding in lifts. Members of same team might need to meet in same conference room, hence lift would be required.)
 - Else in different floors (but try to minimize the difference between min. floor and max. floor)
 - But never in different buildings
- 3) Desired pattern of visiting office of different teams:
- Days in a week when a team wants to be in office (different priorities for different days)
 - Any 'x' days in a week - these days can be consecutive, or spread out across the week.**
 - If a team wants to be in office on a particular day and there is not enough capacity to accommodate all on that day, then either all would be allocated on a different day, or the model would allocate first to that day, and remaining to another day.**
 - Days in a week when a team does not want to be in office (eg: Friday due to high traffic)
- 4) Dedicated seats for employees coming to office daily.
- 5) A small percentage (1-2%) of seats can be reserved as buffer for employees who turn up at the office unexpectedly but were not considered in the input.
- 6) Ensure as much as possible that a team sits in the same floor/wing across most days.
- 7) To maintain social distancing norms, update available capacity of each wing to appropriate value Example: reduce to half.
- 8) Exclude night shift employees from the model as they can occupy the same spaces vacated by day shift employees (since this is a corporate office and not a factory, we can assume that very few employees ~2% would be working in night shift)
- 9) If number of meeting rooms differs across floors => For a floor having more meeting rooms, give preference to teams which need more meeting rooms.
- 10) The model would look at historical model allocation and number of seats actually occupied and use this as a feedback mechanism to improve the outcome in future. Objective would be to minimize unoccupied seats for some teams because the occupancy number they projected was much higher than actual occupancy (Team 1 in example below). These unoccupied seats could have been allocated to teams which occupied all the allocated seats (Team 2 in example below).

	Required	Model allocated	Actually occupied
Team 1	100	60	55
Team 2	100	60	60

- 11) Other factors that the model can consider:
- Priority to employees staying far away from office, expecting mothers etc.
 - Number of employees in the team
 - Historical model allocation and actual occupancy (detailed in point 10 above)

How can Operations Research help in other shared office spaces eg: cafeteria, elevator?

Other shared areas in office might also need similar techniques to enhance employee experience and improve productivity. For example, discrete event simulation can be used to find process bottlenecks in the **cafeteria**. This will ensure that employees spend minimum non-value added time during lunch break. The model would answer questions such as:

- How many counters do we need? Do we have sufficient chairs?
- What would be the utilization% of the counters?
- What would be average and maximum occupancy% of the chairs?
- What is the average and maximum time that an employee needs to wait in different queues?
- Would extending the lunch timings alleviate the bottleneck?

Elevators become a bottleneck specially during lunch hours. Discrete event simulation model can be applied to find best operational policy of the elevators. Example: If a building has 9 floors and 6 elevators, should all elevators be available for all floors? Or odd-numbered elevators for odd-numbered floors, and even-numbered elevators for even-numbered floors? How do we need to tweak the operational policy if 1 or 2 elevators are undergoing maintenance on a day?

JUSTICE DIGITIZATION: USE OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING IN INDIAN JUDICIAL SYSTEM



Rohan

Rohan has close to ten years of experience working in the private and public sectors. He holds a bachelor's degree in Biotechnology and a master's in Nanotechnology from DCE (Delhi). Rohan also holds an MBA from the Indian Institute of Management (Ahmedabad). He is currently pursuing his doctoral research in marketing at IIM-A. Rohan's research interest is in the healthcare sector, particularly in addressing the accessibility and affordability problems through novel interventions that can help upgrade the Indian healthcare ecosystem. He is an author/co-author of about 15 publications and articles, including a research paper for the journal "Seminars in Cancer Biology" (IF-16). He also has over 350 citations.



Anurag

Anurag has over eight years of consulting, government affairs, social sector and public policy experience. Currently, he is working as the Innovation Lead at Atal Innovation Mission, NITI Aayog. He leads multiple strategic initiatives vital to the Innovation and Entrepreneurship Ecosystem building in India. Anurag holds an MBA from Indian Institute of Management -Ahmedabad and M.Sc in International Management from Bocconi Universita, Italy.



The ordinary person craves nothing more than justice. But is a swift, time-bound delivery of justice promised to them? If the Indian judicial system needs to become efficient and proactive, it must become an early adaptor of cutting-edge technologies and tackle its pending cases. It is abysmal if one takes stock of the pendency of cases in India. As per the recent National Judicial Data Grid (NJDG) data, the High Courts in India have about 57 lakh pending cases and about three crore pending cases at the district and taluka levels. Of all the pending cases, Writ petitions constitute the highest pending cases (31.41%) in High Courts, whereas Original cases are the highest pending (86.98%) in District and Taluka Courts of India, as shown in Fig. 1.

Matter Type Pendency Pie Chart

High Courts of India



District and Taluka Courts of India



- Writ Petition
- Second Appeal
- First Appeal
- Appeal
- Case/Petition
- Revision
- Reference
- Suit
- Original
- Appeal
- Application
- Execution
- Review
- Application

Figure 1: Matter type pendency of cases in High Courts, District and Taluka Courts of India (source: National Judicial Data Grid)

High pendency reduces access to justice and ultimately erodes people’s faith in the system. Recently, an unstarred question was asked in the first part of the Budget session of Parliament regarding the usage of artificial intelligence and its potential to reduce the pendency of cases. For years, marketing and sales professionals have used large datasets and advanced data analytical techniques to make more informed decisions. The question is, why legal professionals can’t make use of the same methods? Regarding technology adoption, the legal sector has been a laggard and falls even behind industries such as oil and gas. In this article, we will explore how AI-ML can help streamline the inefficiencies in our judicial system and the benefits of integrating AI-ML in justice delivery.

Steps taken by the Indian judiciary to integrate technology in the past

The then Chief Justice of India, P. Sathasivam, launched the e-Courts National portal on 7th August 2013, based on "National Policy and Action Plan for Implementation of Information and Communication Technology (ICT) in the Indian Judiciary - 2005". The project’s vision was to transform the Indian Judiciary by ICT enablement of Courts. It is a pan-India project funded and monitored by the Department of Justice, Ministry of Law and Justice. The other examples of technology in the judiciary are - SUVAS (Supreme Court Vidhik Anuvaad Software), SUPACE (Supreme Court Portal for assistance in court efficiency) and virtual hearings. During Covid-19, virtual hearings and e-filing have seen a considerable rise. SUVAS is an AI-based system that assists in translating judgments into regional languages, whereas SUPACE helps in digital automation by first understanding various judicial processes that could be automated and then helping the Court improve efficiency and reduce pendency. It puts forward the different judicial processes that could be automated through AI. Currently, only the High Courts, District and Taluka courts are on the NJDG platform.

The E-Committee of the Supreme Court had mentioned in March 2022 that the Supreme Court would also be available shortly on the NJDG platform.

How can the integration of AI-ML in the legal system help?

In the legal domain, a dynamic balance between automation and humans must exist. The idea of using AI-ML in the legal environment is to make processes in the system more agile and rule-based to avoid losing time on tracking and repetitive tasks. Some of the AI-ML use-cases can be found in the following legal scenarios, as shown in Fig.2.

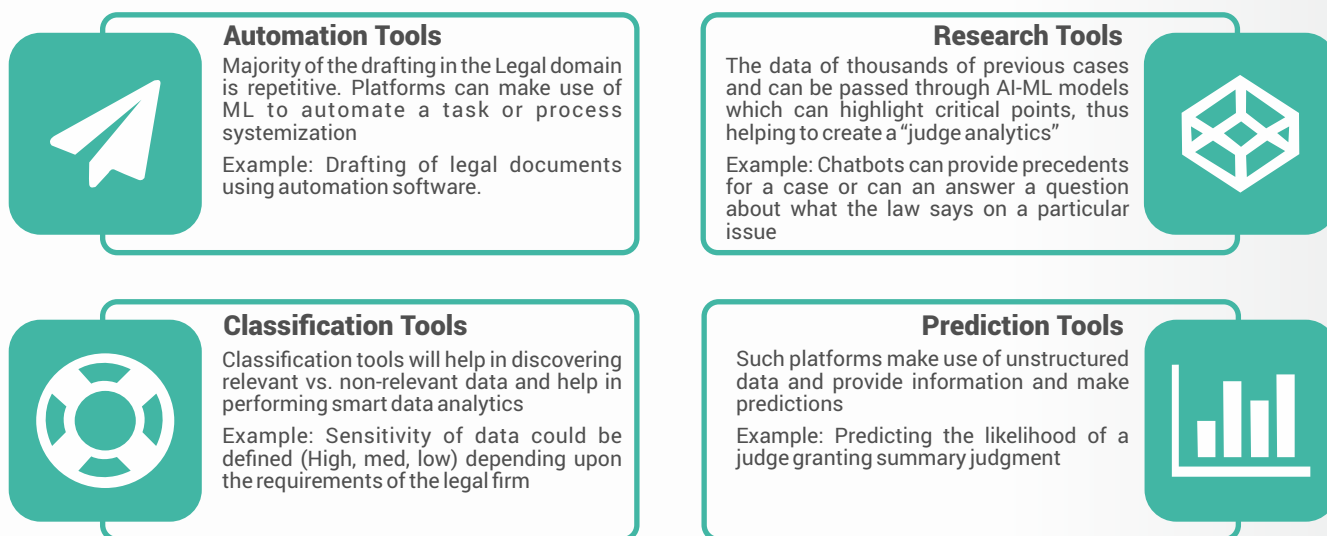


Fig.2. Various AI-ML use-cases that the legal industry could make use of

NLP can assist legal professionals in devoting more time to developing superior legal reasoning, interpreting laws and increasing focus on cases of higher complexity. Tools derived from AI could help expedite the case-flow management and present a more cost-effective, streamlined and time-bound means to the fundamental right of access to justice. Legal research is a heavy-duty task in itself. Passing the data of thousands of previous cases and historical sets of precedents through these AI-ML models can highlight critical points relevant in specific cases and help create a "judge analytics". Imagine a judge equipped with such tools can complete the following things by clicking a button - analysis of factual proposition, determination of appropriate legal provisions and preparation of legal briefs on cases. In the future, it wouldn't be a complete surprise if a judge said, "Hi bot, can you scan this case and let me know the legal precedents for it?"

Stage (Admission/ Regular) of Pending Cases By Supreme Court



Fig.3. Stage of pending cases in Supreme Court split by the stage at which they are spending (source: SCOobserver)

In the specific case of the Supreme Court (SC), it was found that SC had about 70,000 pending cases by the end of 2021 (Fig.3). Interestingly, it was found that 72% of the cases are pending at the admission stage. So, whenever a case is filed in Supreme Court, it is first heard at the ‘admission’ stage and then passed on to a ‘regular’ hearing stage if the court finds that the case involves a substantial question of law. Of all the cases that come to SC at the ‘admission’ stage, only 11% of cases are passed on to the ‘regular’ hearing stage.

This means that the SC spends a significant amount of time on cases which do not get to the next stage, and significantly less time remains for the Court for critical matters. Using AI-ML tools at the admission stage can help the SC move swiftly to clear less critical cases at the admission stage itself.

Where law firms would spend additional funds?*

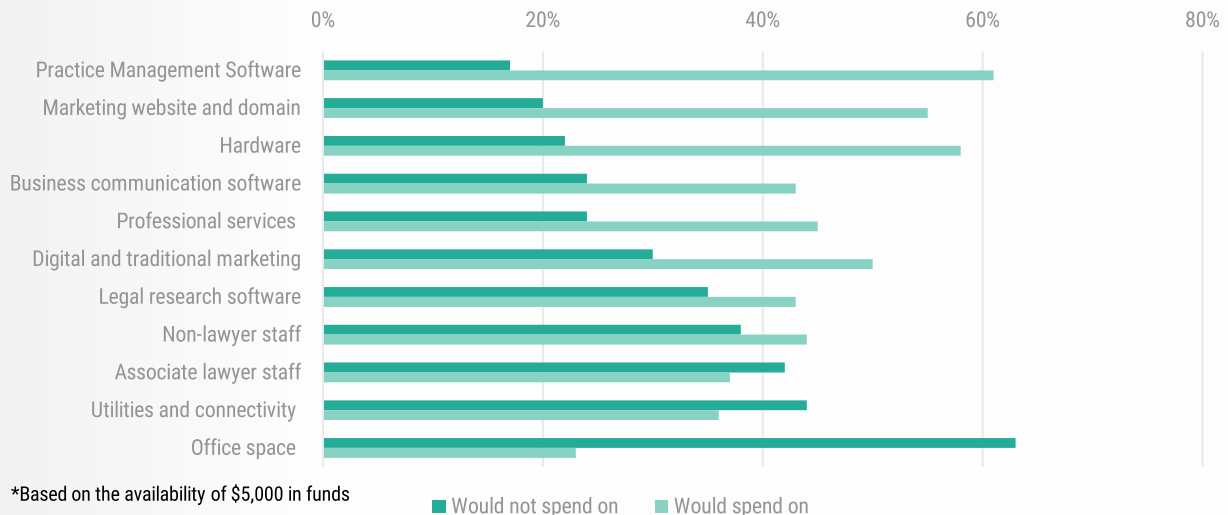


Fig.4. Where law firms would spend additional funds if they had \$5000 in funds (source: Clio)

Not only the courts but legal businesses want to pivot their business around advanced technologies. As per the Legal Trends Report (by Clio) 2021, if firms had an availability of \$5000 in funds (Fig.5), they would prefer to invest in lower-cost investments like legal software and other AI-ML-supported technologies.

Global initiatives of integration of technology with legal systems

The US courts use Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), a case management and decision support tool that helps assess the likelihood of a defendant becoming a recidivist. The UK police forces use the Harm Assessment Risk Tool (HART) to make custody decisions, and it allows police officers to pick if a person should be referred to a rehabilitation programme. China’s Ministry of Human Resources and Social Security uses a facial recognition app, Laolai.com, to ascertain pension payouts and avoid fraud. Singapore State courts’ new 35-storey tower is equipped with a real-time AI transcribing system. It allows judges and parties to review oral testimonies in court immediately as it can transcribe English oral evidence in court hearings in real-time. Earlier, it used to take seven days to provide transcripts of court proceedings as it was done manually while listening to audio recordings. Malaysia has gone a step further as some of the Magistrate Courts have begun to use AI that assists Judges in deciding the appropriate sentences for certain criminal offences. We are witnessing the era of “AI sentencing”, which is scary.

Tread carefully: AI is not the replacement of lawyer

In 2021, the 47th Chief Justice of India, S A Bobde, said that technology should never be allowed to take decisions and that it must be left to judges. Further, he also mentioned that AI should not augment the existing inequality or create new disparities in society. If an analogy is to be drawn, we are not talking about fully automated cars but the use of AI-enabled features such as lane departure warning, rear-drive assistance and forward collision warning. This means that bots don't make legal decisions but help digitise legal documents, quote precedents and digitally scribe legal proceedings. The legal strategy can enormously benefit from augmentation rather than automation, like in the case of cars. As AI technology grows, there are concerns about data protection, human rights, privacy, etc., which will require significant self-regulation by developers of these technologies.

To begin with, AI-ML tools can be deployed in tribunals where there is no need for oral evidence and cross-examination, and consumer courts are other options where such models can be integrated. Rather than going completely "bold" and deploying such tools in the entire judicial machinery, it makes sense for the Indian judicial system to remain "conservative" and first try and deploy these tools where less human intervention is required. Human intervention is necessary in cases where oral evidence and cross-examination are cardinal processes, such as Criminal cases.

Justice retains its value if it's delivered timely. Justice to a dead person is no justice for the person and a compromised justice for his family. As one of the former Prime Ministers of the UK, William Gladstone, rightly said - "Justice delayed is justice denied".

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New Projects:

Financial networks from big data: A multivariate time series based approach

 **Prof. Anindya Chakrabarti**



Financial markets exhibit non-trivial comovement and dependency structure. The standard approach in the finance literature is to consider the market in its aggregate form. A more recent 'data'-oriented approach emphasizes a more granular decomposition of the market so that the aggregate dynamics can be broken down into contributions arising from individual assets. This leads to two analytical problems. First, one has to necessarily deal with a large amount of data such that the process scales with the volume of data (large N and large T where $T \gg N$). Two, analyzing such a large volume of data requires toolkits which are at the intersection of econometrics and machine learning. In this project, the goal is to construct large scale financial networks based on multivariate time series data to capture the dynamics of the system. The main idea is to provide an algorithmic approach to convert time series into networks such that the properties of time series are also inherited by the resulting network. The spectral structure of the comovement network is known to capture, at least partially, the booms and busts in the markets. Here, we take up two specific problems. One, how reliably does the spectral structure reflect the system for the case where $T \sim N$. Two, a large chunk of the literature on networks construction depends on bivariate modelling which is subject to failure due to multiple hypothesis testing. Therefore, an imminent question is how to construct a network with a direct multivariate model.

Multi-period Facility Interdiction Problem

 **Prof. Sachin Jayaswal**



We propose to study a multiperiod interdiction problem, in which the leader (attacker) with a limited interdiction budget decides the sequence of facilities to interdict (destroy) over time so as to inflict the maximum cumulative damage to the follower. The follower's objective is to serve a given set of demand points from the surviving subset of facilities the minimum cumulative cost across all periods. For this, his decisions include the assignments of demand nodes to the surviving facilities and the allocation of his limited budget to the revival of interdicted facilities and the protection of the surviving facilities against their interdiction in the future periods. The multi-period version of the problem, which is the focus of the proposed study, presents additional complexity due to the leader's interdiction decisions constrained by the follower's protection decisions. The objective of the proposed study is to design efficient exact solution methods for this challenging bilevel integer program.

Data-driven auction design: A computational approach

 **Prof. Jeevant Rampal**



Details: Auctions are often used to sell property rights for liquor licenses, spectrum licenses, land and mineral rights, and construction projects etc. This project investigates potential improvements in these auctions using a computational data-driven approach. The first part of this project will be to collect primary data of the participants and their choices in auctions. Subsequently, using the game-theoretic properties of the chosen auction design, we will computationally estimate the true (unobservable) value distribution across players of the object(s) being auctioned (e.g., liquor licenses). The estimation method used will be non-parametric "distance minimization" between the observed out-of-sample distribution of bids, and the predicted out-of-sample distribution of bids using optimally calibrated parameter values. E.g., Athey, Levin, and Seira (QJE 2011) use their estimated model to make comparative static predictions and test that for fit against data from timber auctions.

Finally, to analyse which auction design would have best met the various aims of the auction designer, we will use the calibrated model, parameters, and the estimated valuations of the bidders. In particular, using these we will simulate the revenue, efficiency, and other metrics of importance for different auction designs. In addition to the use of simulation described above, to analyse alternate auction designs, we will use simulations of variations of the estimated model, parameters (like risk aversion, budgets etc.), and value distributions to analyse the different rates with which different auction designs can meet the various possible aims of the auction designer.



Ongoing Projects:

**Can an AI Coach Help You Lose More Weight Than a Human Coach:
Empirical Evidence From a Mobile Fitness Tracking App**

 [Prof. Anuj Kapoor](#)

High-frequency trading: Measuring latency from big data

 [Prof. Anirban Banerjee](#)

Causes, Symptoms and Consequences of Sociocultural polarization

 [Prof. Samrat Gupta](#)

Employee Reviews - A Text Mining Perspective

 [Prof. Adrija Majumdar](#)

When A Machine Knows When You Are Happy (vs. Upset)

 [Prof. Hyokjin Kwak](#)

Models of implied volatility and information content of option prices

 [Prof. Sobhesh Kumar Agarwalla and Prof. Vineet Virmani](#)

Hiring for the Future – A People Analytics Approach

 [Prof. Aditya Christopher Moses](#)

An iterative gradient-based bilevel approach for hyperparameter tuning in machine learning

 [Prof Ankur Sinha](#)

CONDUCTED SEMINARS



CDSA Webinar
Youtube channel

Polarization in Covid Vaccine Discussions on Twitter

Dr. Piyush Anand (Rice University)

A Bias Correction Approach for Interference in Ranking Experiments

Dr. Hema Yoganarasimhan (University of Washington)

Consumer Reviews and Regulation: Evidence from NYC Restaurants

Dr. Chiara Ferananto (Harvard Business School)

Auditing and Designing for Equity in Resident Crowdsourcing

Prof. Nikhil Garg (Assistant Professor, Cornell Tech Jacobs Technion-Cornell Institute)

Using Explainable AI – To understand what your brain cares about

Dr Saikat Ray (Department of Brain Sciences, Weizmann Institute of Science, Israel)

Quantum Key Distribution: A paradigm shift in secure communication

Dr Ravindra Pratap Singh (Professor, Physical Research Laboratory)

Can machines learn to see without humans teaching them?

Dr Ishan Misra (Research Scientist, Facebook AI Research)

Advances in AI for Social Cyber-Safety

Prof. Srijan Kumar (School of Computational Science and Engineering at Georgia Institute of Technology)

Programmatic High Impact Information Systems Research Using Data Science to address Grand Challenges (November, 2021)

Prof. Sudha Ram (Anheuser-Busch Endowed Professor of MIS, Entrepreneurship & Innovation in the Eller College of Management at the University of Arizona)

Summer School on Large Scale Optimization May 06-13, 2022

There was an enthusiastic response to the summer school held at IIM Ahmedabad, May 06-13, 2022. The program provided rigorous training to the cohort in solving complex real-world optimization problems through contemporary solution methods. To this end, the program provided tutorials on several topics, like Lagrangian Relaxation, Benders Decomposition, Column Generation, Dantzig-Wolfe Decomposition, Cutting Plane Methods, Generalized Benders, Bilevel Optimization, etc. The workshop will give a comprehensive overview for solving large-scale Mixed Integer Linear Programs (MILPs) and Mixed-Integer Nonlinear Programs (MINLPs). Each session on a given topic will be followed by a research talk on a problem that demonstrates a successful application of the method. The next summer school is planned at IIT Kanpur in 2023. Brij Disa Centre of Data Science and AI works closely with the Summer School and extends its support towards this initiative.

Target Audience

- Masters/PhD students in Operations Research/ Management Science/ Industrial engineering
- Faculty Members working with Integer Programmes
- Industry Professionals in Optimization/Logistics/Supply Chain Domain

Faculty

- Prof. Amit Kumar Vatsa, Indian Institute of Management Indore
- Prof. Ankur Sinha, Indian Institute of Management Ahmedabad
- Prof. Ashutosh Mahajan, Indian Institute of Technology Bombay
- Prof. Faiz Hamid, Indian Institute of Technology Kanpur
- Prof. Goutam Dutta, Indian Institute of Management Ahmedabad
- Prof. Jyotirmoy Dalal, Indian Institute of Management Lucknow
- Prof. Sachin Jayaswal, Indian Institute of Management Ahmedabad (Co-ordinator)
- Prof. Saurabh Chandra, Indian Institute of Management Indore
- Prof. Yogesh Kumar Agarwal, Jaipuria Institute of Management (Retd., IIM Lucknow)



Prof Sachin Jayaswal
Co-coordinator
Faculty, IIMA





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