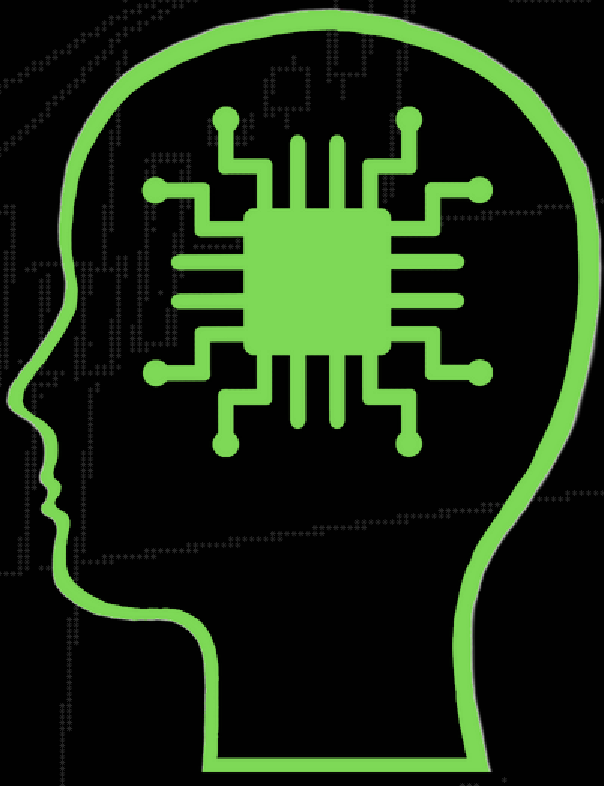
DAY TRADE WITH AI



SHUNYU TANG

Day Trade With AI

Part I

Theoretical foundations for discretionary, algorithmic, and diversified trading with AI

Shunyu Tang

Day Trade With AI

By Shunyu Tang

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DEDICATION

I would like to dedicate this book to my father Hao Tang, who cultivated my passion for computer science and finance; and my mother Wen Peng, who inspires me to pursue my dream.

About the Author

Shunyu Tang is a computer science enthusiast who strives to make day trading a solid science founded on the interdisciplinary fields of finance and data science. As a technical writer and quant trader, he is ranked by Medium as a top writer in Finance and Algorithmic Trading. He is also the editor of a Medium publication, *AI Advances*, which publishes advances in AI and its applications in all facets of modern society.

Acknowledgments

I appreciate my father Hao Tang for supporting my enthusiasm toward programming and encouraging me to turn my projects into writings that can benefit others. When my computer science and day trading passions began, he provided me with hardware and literature so I can continue doing what I love. While dipping into these areas, especially after gaining the first-hand experience of being a day trader, I deeply understood how difficult and stressful day traders are in their trading careers. I learned that the "no free lunch" rule applies everywhere, and years of dedicated education and practice are needed to excel in any professional field.

I appreciate my mother Wen Peng for her endless love and open-mindedness. She is certainly not a "tiger mom" as many Asian parents are. I have many degrees of freedom in searching for my own passions beyond my non-valedictorian academics. She teaches me persistence and resilience in silence. In my childhood, while my father frequently traveled internationally or domestically for months for his start-up business, she undertook all family responsibilities and handled difficult scenarios like a breeze.

I am thankful to my younger brother Evan Tang, who is an avid chess and esports player and a profitable day trader without AI assistance on simulators at the time of this writing. His experience is a showcase to me of how he successfully manages his emotions and risks in highly competitive environments, which are the characteristics that I need to keep learning from him. He is also my strong supporter and helper while I was coaching the kids in our neighborhood on chess.

In addition, I would like to thank Mr. Keith Ensminger, my computer science teacher at Cumberland Valley High School, who reinforced my passion for the domain of computing and AI; and Dr. Yongtao Cao, my research advisor at Indiana University of Pennsylvania, who introduced the cutting-edge concepts of quantum computing to me and guided me on how to do research in the domain of computer science and statistics.

Last but not least, I especially need to thank you, the reader of this book. Your purchase of this book is strong support of my work and makes me feel I have done something useful to the field of your interest.

About the Cover Illustration

I created the cover illustration using ASCII characters. The horror font style of the book title indicates day trading is an inherently dangerous activity. The line sketch of a human brain with a chip inside means the purpose of the book is to empower human traders with sophisticated computing power from artificial intelligence (AI). The background candlestick chart means we are applying AI to the context of trading in the stock market.

About the Book

Book Description

This book is aimed at retail traders, data scientists, students, and practitioners alike who want to harness sophisticated AI in the realm of day trading in the stock market. The book assumes the readers have some familiarity with the Python programming language. For reference and review, the appendices contain cheatsheets on Conda, Python, NumPy, Pandas, Matplotlib, Scikit-Learn, and PyTorch.

The book consists of two parts. Part I delivers the theoretical foundations for discretionary, algorithmic, and diversified trading with AI while Part II gives readers the hands-on experience in building a complete AI system for day trading. Readers will find this book useful as it bridges well-established modern finance theories with cutting-edge data science. The strategies that make up the software do not come out of the blue but are solidly founded on the efficient market theory and behavioral finance as two sides of a coin.

Although the book discusses sophisticated machine learning and deep learning algorithms for trading model development, the author uses plain language with minimum math for clear explanations. The code snippets in the listings are reusable and can be easily deployed by readers in their algorithmic systems. From the book website, readers can find Python code, figures and animations, errata, new publications about day trading with AI, and additional information about the book. End-of-chapter exercises are used throughout the book to reinforce key technical concepts, and the solutions are available in Appendix E at the end of the book for self-checking. The book is a comprehensive hands-on guide to making AI a personal assistant to trading.

Contents of This Book

Part I covers four chapters as essential theoretical preparations prior to the development of a complete AI system for day trading.

Chapter 1 overviews the fundamental knowledge required for day trading with AI. Topics include the financial markets, types of activities in the markets, psychology, modeling and algorithms, and tools and packages to build an AI system for trading.

Chapter 2 discusses the fundamentals of discretionary trading. It starts with the technological aspects of trading including time windows, static features, and dynamic features, which are pre-requisites of coding an AI system. Commonly used pattern strategies, psychological pitfalls, and risk management methods are also discussed.

Chapter 3 is an introduction to algorithmic trading. With a correctly defined mindset of using algorithmic trading, we start the chapter with regression and classification as the basics of machine learning and deep learning tasks and employ simple gradient descent and normal equation methods to solve sample trading problems. Then, we delve deeper into more complicated machine learning and deep learning algorithms and evaluate their performances. After discussing feature engineering, we proceed with the strategies to build AI and non-AI models.

Chapter 4 establishes the theoretical foundation for day trading with AI by creating a realm of diversified trading that includes stock, model, and time diversification to ensure an edge toward success. Solidly grounded on the finance theories developed by the fathers of modern finance, independent models are developed by extrapolating the Nobel-Prize-winning principles and the cutting-edge large language models to the context of day trading. At the intersection of modern finance theory and data science, a paradox is unveiled so that we strive toward building independent models to tackle the randomness in financial data.

Conventions Used in This Book

The following typographical conventions are used in this book:

Italic

Indicates new terms, URLs, email addresses, filenames, and file extensions.

`Constant width`

Used for code blocks, as well as within paragraphs to refer to program elements such as variable or function names, databases, data types, environment variables, statements, and keywords.

`Constant width narrow`

Shows output generated by the code.

Using Code Examples

I write this book to help you build your algorithmic system. In general, you may use the code in this book in your programs and documentation. You do not need to contact me for permission unless you're selling or distributing examples from the book. For example, writing a program that uses several chunks of code from this book does not require permission. Answering a question by citing this book and quoting example code does not require permission. Incorporating a significant amount of example code from this book into your product's documentation does require permission. If you feel your use of code examples falls outside fair use or the permission given above, feel free to contact me.

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How to Contact Me

I welcome any questions or comments concerning this book. Please use the contact form on the book website and I will get back to you as soon as possible.

For more information about my new publications, news, and events, follow me on:

Medium: *https://shunyutang.medium.com*

Twitter: *https://twitter.com/shunyutang*

LinkedIn: *https://linkedin.com/in/shunyutang*

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Preface

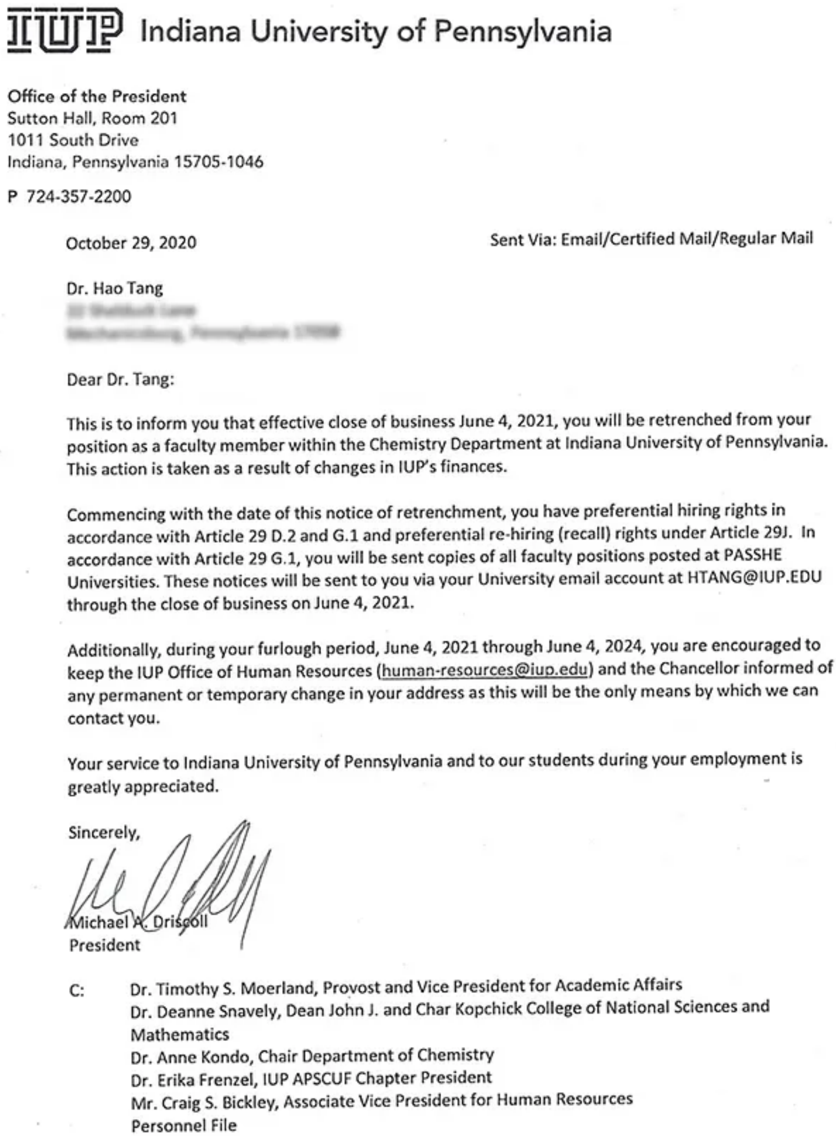
A Tale of Four Andrews – My Journey of Enthusiasm

While being obsessed with coding bots for my Discord server, I heard an unpleasant chat from downstairs, though the voices were faint and intermittent. It was a conversation between my parents. My mother Wen, proud of keeping a "full-time job" raising two sons for over 14 years, was very much anxious, with a depressing tone that was never heard before. My father Hao, a professor in the chemistry department at a state university in Pennsylvania, soliloquized about moving to Mississippi after being notified of a retrenchment decision. He was quite upset that his immense contributions to the university could not make up for his low seniority among his colleagues, upon which the retrenchment decision was made. It turned out the quarrel started when he could not convince my mother without first convincing himself of a delusionary bright future of another speciously stable job. The 2020 pandemic made everything uncertain. I was relieved days later when I heard he did not get the Mississippi offer and thus the moving plan was postponed. To me, there would be too much to give up again, just like what was lost during the previous move from Minnesota to Pennsylvania in 2017: the friendship, the mentorship, and the honors and opportunities as I was planning on earning more Minnesota statewide chess tournament titles.

Growing up in a family of first-generation immigrants to the U.S., my past 17 years were never short of moves while my parents were in pursuit of the American dream. I was born in a small town called Dongzhi in Anhui province in central east China. At three years old, I was brought to Algiers, Algeria to live with my grandparents (Figure 0-1).

Figure 0-1. My Algeria visa on a Chinese passport

My grandfather Zhengwu was a construction worker deployed to Africa by China to build the East-West Highway (also known as the A1 Highway) for Algeria. From Algiers, I boarded the airplane to the U.S. for the first time to join my parents, who at that time were on student visas striving for a U.S. diploma and a stable job. However, it was in my memory that such a stable job never came. The hardship in my childhood taught me the first lesson that financial stability is difficult! As a social being, I had a keen interest in watching how other people made a living. In early 2021, many of my classmates were talking about *meme stocks* such as Game Stop and AMC and I knew a few of them actually day-traded these stocks and made quite a lot of money. This was contradictory to my belief that no one can make money easily. Thanks to the subtle education I received in a family of a professor, I knew in the vast ocean of knowledge, I can't stop learning! Driven by the desire of alleviating the financial hardship during my father's layoff period, I taught myself many materials through online learning, hoping the new knowledge could empower my existing coding strength and help my family go through the difficult period (Figure 0-2).



Indiana University of Pennsylvania

Office of the President
Sutton Hall, Room 201
1011 South Drive
Indiana, Pennsylvania 15705-1046

P 724-357-2200

October 29, 2020

Sent Via: Email/Certified Mail/Regular Mail

Dr. Hao Tang
[redacted]

Dear Dr. Tang:

This is to inform you that effective close of business June 4, 2021, you will be retrenched from your position as a faculty member within the Chemistry Department at Indiana University of Pennsylvania. This action is taken as a result of changes in IUP's finances.

Commencing with the date of this notice of retrenchment, you have preferential hiring rights in accordance with Article 29 D.2 and G.1 and preferential re-hiring (recall) rights under Article 29J. In accordance with Article 29 G.1, you will be sent copies of all faculty positions posted at PASSHE Universities. These notices will be sent to you via your University email account at HTANG@IUP.EDU through the close of business on June 4, 2021.

Additionally, during your furlough period, June 4, 2021 through June 4, 2024, you are encouraged to keep the IUP Office of Human Resources (human-resources@iup.edu) and the Chancellor informed of any permanent or temporary change in your address as this will be the only means by which we can contact you.

Your service to Indiana University of Pennsylvania and to our students during your employment is greatly appreciated.

Sincerely,

Michael A. Driscoll
President

C: Dr. Timothy S. Moerland, Provost and Vice President for Academic Affairs
Dr. Deanne Snavely, Dean John J. and Char Kopchick College of National Sciences and Mathematics
Dr. Anne Kondo, Chair Department of Chemistry
Dr. Erika Frenzel, IUP APSCUF Chapter President
Mr. Craig S. Bickley, Associate Vice President for Human Resources
Personnel File

Figure 0-2. My father's retrenchment letter that brought a nightmare to us during the pandemic

I was not a novice at the time and had already gained some passive cash-making experience through my coding skills. I had coded a bot that automated web searches to receive commissions at a payout of a few dollars per month. I had also coded a bot that notified me when an out-of-stock long-awaited graphics card re-appeared at Best Buy at a discounted price so that I could snipe it within seconds to resell. I even contacted local businesses with an offer to repair their computers (Figure 0-3). To grow my ability of earning, I offered my father a news-scraping bot to gain an information advantage because stock prices are certainly moved by the news. He heavily invested in stocks of the technology sector and lost big, which exacerbated the financial hardship. He was excited about the idea and could not resist trying my bot as his trading assistant. Trading is inherently difficult. But that experience was just a kickoff.

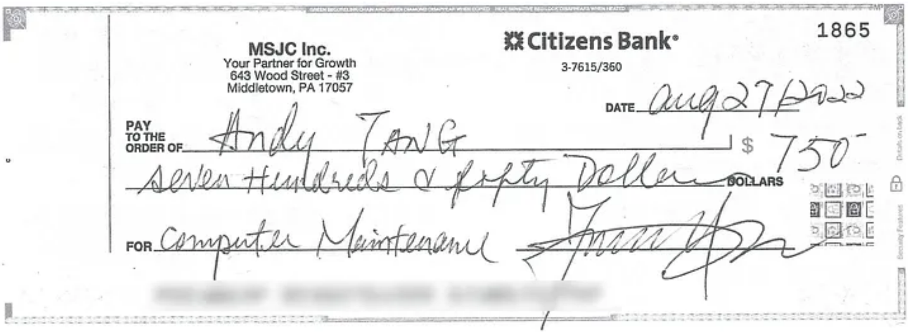


Figure 0-3. I was an ad-hoc computer repair specialist for a local business during the pandemic. For the whole Saturday afternoon on August 27, 2022, I repaired 10 computers for the business and earned $750. This wasn't bad because the hourly rate was about $150!

In a frenzy for knowledge, I taught myself artificial intelligence (including machine learning and deep learning), data science (including statistics), computer science, finance, and trading. Most importantly, I strived to combine what I learned into one piece of knowledge for application in the stock market. Through what I've learned, I was heavily influenced by Andrew Ng's Machine Learning course on Coursera, Andrew Lo's Finance Theory course at MIT OpenCourseWare, and Andrew Aziz's book *How to Day Trade for a Living*. It seems that all of these Andrews are to whom I owe gratitude and what a coincidence that my nickname is Andrew too. I once asked my father why he gave me the name Shunyu and the nickname Andy. He replied that in Chinese "shun" means "follow" and "yu" means "universe." As a Christian, he hoped the only God in the universe would give me instructions that I just need to follow. So, "Shunyu" (aka following the universe) is the original literal meaning of my official name. The Head Start program at Fink Elementary School in Middletown, Pennsylvania was where I began using my nickname, Andy. Handing me over to the teacher on my first day of school in the U.S., my father replied for me to the teacher's query about my name: "He just came here from Africa and thus can't speak English. You can call him Andy." In fact, later, I knew he wanted me to get more attention from the teacher because he believed teachers preferred calling students' names alphabetically, and the last name Tang obviously did not offer any advantage. That was why my first name must start with an "A" to make up!

With regard to the other three Andrews who are my influencers, I happened to know their childhood stories as well, from which, surprisingly, I can see some resemblances with mine.

Andrew Ng is a pioneer in Artificial Intelligence education, an entrepreneur, and a professor at Stanford. His machine learning course on Coursera has reached millions of audiences. He was a son of an immigrant family as well. As a result of his parents' immigration from Hong Kong to Singapore, he received his childhood education in Singapore and then for higher education, he came to Carnegie Mellon University in the U.S. to study Computer Science. I remembered how excited I was when my first gradient descent code worked to optimize the parameters of a linear model following the algorithms he outlined in his course.

Andrew Lo is a pioneer in creating the "*Adaptive Market Hypothesis*" (*AMH*) and a professor of finance at MIT. His finance theory course 15.401 is one of the most popular courses at MIT OpenCourseWare. He spent his childhood in a single-parent family without extra cash in Brooklyn, New York. At the age of 6, he nagged his mother for a jacket with an emblem of Superman. When his mother finally bought him that jacket after work on a Friday afternoon, he was so happy about it that he wore the jacket for the whole weekend, even in his sleep. On Monday morning, he was still trying all kinds of poses with the jacket and unfortunately was late for school. He said he was completely mortified on that day and always appreciated the very negative feedback which drove him to come up with the AMH, of which behavioral finance is the other side of the efficient market coin.

Andrew Aziz is a pioneer in day trading education, an entrepreneur, and a mountaineer. His book *How to Day Trade for a Living* is a bestseller on Amazon for day trading beginners. He had a miserable childhood in a refugee camp during the Iran-Iraq War. When he grew up, he immigrated to Canada from Iran for higher education. He studied chemical engineering at the University of British Columbia and received his Ph.D. However, a layoff changed his career path completely from the academics of chemical engineering to the practitioning field of day trading. He is a person never scared of pursuing unquantifiable risk, as evidenced by his recent conquering of Mount Everest.

Knowing the similarities of myself to the other three Andrews' childhoods and standing on the shoulders of these pioneers, I felt motivated because I think I can do something as well. As part of a young generation of traders and technology lovers, I am always intrigued by the practical limits of new technologies, especially the recent technological breakthroughs of AI. I noticed a tendency for people to ignore the comprehension and utilization of the established theories but delve into pattern recognition where there was little theoretical support. There is a misbelief that the power of data science can do anything, including beating the market. I was thinking if AI was really so powerful, the people who developed it, like the software engineers who developed the AlphaGo, must have succeeded in trading with AI already and they must have been billionaires and sooner or later they will be wealthier than God himself. I know that can't be possible. Thus, pure software engineers and data scientists do not have an edge when they try to apply their most sophisticated AI to the context of trading. In fact, Yann LeCun, the Father of Convolutional Neural Networks and a Turing Award recipient commented in a talk that AI is still at the dog level, if not rat level. Since AI has a long way to go before reaching the human level, it is unrealistic to expect a God-level AI to trade for me in the stock market. When I took a Robotics online course taught by Howie Choset, Professor of Computer Science at Carnegie Mellon University, I especially loved the talks given by the guest speakers he invited. Those speakers were top researchers in the field of robotics and AI, and I remembered vividly their endeavors were toward something like a robot waiter serving wine in a restaurant. It was extremely difficult for a robot to do it as naturally as humans without spilling or damaging the glass. This is another piece of evidence that a 6-year-old kid can do what most sophisticated AI can't.

Since pure software engineers and data scientists don't have an edge in the stock market, what about professionals in finance? In Andrew Lo's Finance Theory class at MIT, Professor Lo once asked the class who the next Warren Buffett would be and a student responded "Andrew Lo." The class laughed. Andrew joked "Those who can't do, teach. Those who can't teach, teach gym. At least, I don't teach gym." Obviously, I can deduce the most sophisticated pure finance professionals can't have an edge in the stock market; otherwise, there won't be professors in finance.

But who can make money from the stock market? This is the most important question I need to answer before I delve into the stock market further. Andrew Lo said Warren Buffett and James Simons can, and Andrew Aziz demonstrated himself as a consistently profitable trader. Warren Buffett's strategy is picking stocks and holding the stocks until he wins. James Simons's strategy is using the algorithms developed by hundreds of PhDs in multidisciplinary fields. Andrew

Aziz's strategy is discretionary trading by controlling the inherent pitfalls of human psychology.

Warren Buffet's horizon is somewhere like 20 or 30 years of investing, which I don't have the patience for. I prefer James Simons and Andrew Aziz's style of trading, which has a horizon as short as a few minutes! The difference is James Simons has sophisticated proprietary algorithmic models to make decisions while Andrew Aziz has his mental model to make decisions.

It turns out these folks are not in one specific field but are experts in multidisciplinary fields. James Simons's success demonstrates the feasibility of algorithms or essentially, AI for gaining an edge in the stock market. However, if I want to be like him, I can't just be a pure computer scientist or data scientist unaware of established finance theories. I believe finance theory is the key to guiding data science practitioners out of the maze, and I can trust the result of my model more because it is produced from explainable and interpretable algorithms. I applied Harry Markowitz (the Father of Modern Portfolio Theory)'s mean-variance analysis for building an investment portfolio to a day trading context for risk management. I also applied Black and Scholes's options pricing formula to a day trading context for the detection of early signals of trend changes. I further extrapolated the bond idea of separating junior tranches and senior tranches to the definition of trading success so that the success rate can be substantially increased. Many more of such ideas are shown in this book. None of these creative endeavors are possible without the preparation of some financial foundation by taking Andrew Lo's course. And most importantly, they work well.

Many times in live trading, I was thrilled to see my model give me the perfect highest and lowest predictions and even the exact time to reach those levels (e.g., see my live trading recap[1]). I wondered why this happened. My explanation is that if my model can detect them, the models trained by other sophisticated people can too. That would trigger us into either buying or selling the stock at the same time, which made what was predicted to happen, happen. Evidence for this explanation is whenever my model failed, which could also happen many times, the squeeze in the stock would be huge because other models would predict the same thing and those algorithmic traders must stop out of their positions at the same time.

So why should I still develop a model knowing it could be right or wrong and may not be as sophisticated as the ones that the smartest minds developed? I consider model development a necessity for explaining a view from a higher dimension.

[1] *https://youtu.be/8oXRaeFWKVA*

Take the formation of the "*death spiral*" by a group of army ants as an example. Such a group of army ants may be separated from the main foraging party, lose the pheromone track, and begin to follow one another, forming a continuously rotating circle, known as a "death spiral," and may eventually die of exhaustion. If I am an ant in the "death spiral," the only way to get out of this is to be informed of the "spiral"—a piece of information from a higher dimension—an angle-of-view from a human. The analogy here is that the model will provide such information for traders from a higher dimension—a dimension that human traders cannot perceive easily. If I know my model predicts one level as the lowest price, I can expect the mass of other algorithmic traders to buy at that level. Despite that the model can be right or wrong, it provides one dimension of information that discretionary traders do not have. Thus, it is useful. One of my classmates, knowing I strive for developing a robust algorithmic trading system, asked if my system was fully automated or human-supervised. I replied that I needed to intervene. He said it would be better if it were fully automated. Well, it would certainly be nice if I could make money in my sleep. However, I know where my limitations are, and thus can't dream of something unrealistic. As far as I know, even the most sophisticated, fully automated algorithmic trading systems have human traders sitting behind them watching every trade they execute. In Andrew Lo's class, I learned about the stock market crashes in 1987 and 2008, and that the associated casualties of human lives were related to the algorithmic systems. As the system was programmed to buy when everybody else was selling, you can't blame the system because it was just doing its job! That's why I titled my book "Day Trade **With** AI," not "Day Trade **By** AI" because I am still the individual who makes the final trading decision. The AI just gives me some advice to keep me informed of the common sense of what other algorithmic traders might do.

With that said, trading is still a psychological game, regardless of whether or not I use an algorithmic system. Andrew Aziz influenced me in that I should not ignore the training of personal traits in handling stress. There are so many psychological pitfalls in trading. We humans are hardwired to lose in the trading game inherently. According to Andrew Aziz, "adding to a losing position" and "letting the losers run while keeping the winners short" are the top two sins of human traders. Andrew Lo summarized three traits of human traders: (1) prefer more money to less (greed), (2) prefer money now to money later (impatience), and (3) prefer to avoid risk (risk aversion). At some point in my trading endeavor, I realized these three traits were exactly what the smartest minds in the market utilized as an edge to succeed. I must avoid falling into these pitfalls and consider joining the smartest minds to trade against these people because trading is a zero-sum game.

Coming back to my goal of developing an ultimate trading bot for alleviating the financial hardship of my family, it is obviously not an easy job and I have to keep learning and practicing. It was good to hear that the university decided to rescind my father's retrenchment letter seven months later. Since the imminent financial hardship issue was gone, my family did not have to move. But thanks to that stressful experience, my trading model's version number has gone up from version 1 to version 7 and will continue. I've found a lot of fun in model development and can't stop! While most of the time I was using my father's simulator account to trade in the live market conditions, I'd like to use Harry Markowitz's story detailed in Professors Andrew Lo and Stephen Foerster's book *In Pursuit of the Perfect Portfolio* to encourage myself. When Markowitz developed the mean-variance analysis approach to build an investment portfolio in 1952, he was a Ph.D. student with no real stock investing experience. However, the approach he developed established the finance career and won him the Nobel Prize in Economic Sciences in 1990. I've recently learned from Professor Stephen Foerster that Professor Markowitz passed away on June 22, 2023, at the age of 95. While this preface is being written on July 4, 2023, it is also in memory of Professor Markowitz for inspiring millions, if not billions of young people, to step into the field of finance.

That's me, an eternal learner at the intersection of computer science, artificial intelligence, data science, finance, and trading, on the journey of enthusiasm shaped by three senior Andrews. Just like I teach myself the materials I write, I hope I can inspire my readers on pursuing their interests regardless of their educational background.

Part I

Part I of the book covers four chapters: the fundamentals, discretionary trading, algorithmic trading, and diversified trading. It delivers essential theoretical preparations prior to the development of a complete AI system for day trading. Note that day trading is not yet regarded as a solid science. Instead, it is considered to stay in the same category as gambling because we can't argue that according to modern finance theory, most of the time the stock prices follow a random walk and the historical price data contain no predictive information. With unavoidable commission and slippage costs, trading is inherently a losing game. However, there is still a small percentage of consistently profitable traders inclusive of both retail traders and institutional traders. It turns out their successes were not due to luck—they either have their brains free of the pitfalls that are hardwired in most other people or have an edge to capture the short-lived arbitrage opportunities in the stock market using the computing power of machines. These four Part I chapters will explain why that can happen from theoretical perspectives so that in Part II to follow we can code our findings from Part I into the software.

1

The Fundamentals

1.1 The Financial Markets

Trading is a series of buy-and-sell activities with profit as the only goal. Historians believe trading emerged since around 3000 BC and is undoubtedly one of the most ancient human activities. In the modern world, trading occurs in many different forms. Since the start of the *financial markets* in the U.S. in 1790 the Philadelphia Stock Exchange, or even earlier into the 17th century when continuous trading on the stock of the Dutch East India Company occurred on the Amsterdam Exchange, people could trade intangibles in addition to physical commodities. As technology evolved, tens of thousands of financial products are now available for people to choose from, and the trading process is as simple as a few mouse clicks online. What's amazing is there is no more need to stockpile gold at home to protect your assets from inflation—simply buying a gold *ETF* (*exchange-traded fund*—a type of investment fund traded on the stock market) will achieve the same effect. In fact, you can buy any asset in an intangible form from the financial markets without actually holding the corresponding tangible assets that may cause unnecessary hassles to you like storage and transportation. Of course, everything comes at a price. There is no free lunch. The hassles saved on you have already been incorporated into the price of the financial products. With that said, this book deals with trading stocks instead of physical commodities. In addition, I exclude the trading of forex, bond, options, and futures, since all thoughts in the book are based on a stock-trading perspective.

Due to the ancient feature of trading, it sounds intuitive that it may be the easiest thing that people can do for a living. It appears that trading does not require advanced knowledge of mathematics, science, history, engineering, and technology because our ancestors did not have those, yet they could still trade by simply following one principle: “buy low and sell high.” Is that really the case? There are two factors we need to consider: survivorship bias and value creation. If we treat trading as an easy job due to the above logic, we may have fallen into the trap of survivorship bias, as we only focus on a few successful traders without considering the other millions or billions who didn’t survive in the event. On the other hand, the ancient forms of trading on physical commodities such as grain and beef are a reflection of the value that was created through prior work. They earned what they deserved through the hard work that created the value of grain and beef. They are different from the traders today, who profit from price fluctuations while negligible value creation is involved in the trading process. Furthermore, the “buy low and sell high” principle is extremely misleading. A novice trader may find trading easy as the price patterns frequently demonstrate a sine wave shape with periodical peaks and valleys. “Just buy at the valleys and sell at the peaks!” the novice trader says. The problem is we cannot see into the future. Peaks and valleys are explicit only after they are formed. With any given segment of a sine-curve-like price history, the next moment the price may either go up or down, making it essentially a guess of the head or tail of a coin. The reason is numerous smart people are participating in trading activities, and if the odds are not 50/50 at any moment, say 60% up/40% down, some people who notice it will immediately take advantage of the imbalance by consistently buying a lot of the stock and the net positive profits will make them the winners. The traders who sell their stocks to the winners are the losers because they lose the upside growth value of the stock by selling most of the time. There are two outcomes for these losers: either they continue losing by selling when they see the same pattern appears again, or they become smart and start buying instead of selling. Since all these people are smart, if such up-favorable odds really occurred and lasted long enough until everyone realized when the pattern re-appeared and everyone wanted to buy but no one wanted to sell, then guess what? No trade would happen! This overrides the original assumption and explains why the hypothesis of imbalanced odds is not true and we must accept the 50/50 odds most of the time. That’s why trading is so hard because, to most people, it is like a game that gambles on heads or tails!

Through the above hypothesis analysis, you may have realized that the imbalanced odds may appear, but are short-lived, before most people can notice and take advantage of them. That’s why there are so many professionals employing all kinds of tools and resources, searching for these imbalances. Undoubtedly, we are part of them. Before we can do that, let's understand the financial markets further.

Financial markets provide *securities* products to investors and lenders who have excess funds and wish to get returns through buying these securities. In the meanwhile, the financial markets make these funds available for businesses and entrepreneurs (the borrowers) who need additional capital to expand or facilitate the smooth operations of their businesses. Some financial markets are very active, where trillions of dollars of securities are traded daily, such as the *New York Stock Exchange* (*NYSE*). Traders love such markets because active markets provide sufficient *liquidity*, which means traders can buy and sell securities quickly without causing a drastic change in the transaction price. The "*liquid*" concept also applies to any valuable products. *Cash*, for example, is the most liquid financial product because you can exchange cash for any other products of value instantaneously. A used bike, on the other hand, is not that liquid. If you want to trade your used bike for a decent value of cash, the best place to go is the used bike market, which has more liquidity (i.e., more buy-and-sell activities of used bikes in this case), and you can get a fair value of cash out of it. The logic is the same for stocks. It is beneficial to go to a liquid stock market for stock trading. This is especially important for day traders who frequently buy or sell stocks using their entire account size in a matter of minutes or even seconds while the market price is barely moved. Only a very liquid market can meet such needs.

Traders benefit from the price fluctuations in financial markets. For stocks, we specifically refer to the *stock market*—the only financial market discussed in this book. Why do stock prices change? A "supply-and-demand" theory easily explains it: If more people want to buy a stock (the *demand*) than sell it (the *supply*), the price moves up, and vice versa. Such an explanation certainly does not offer extra hints for a trading decision. How do we know when more people want to buy a stock? To answer this question, we need to understand all parties participating in trading activities in the stock market.

Let's focus on three moments of a trading day on NYSE. Note that despite the normal trading hours of 9:30 am to 3:59 pm U.S. Eastern Time, there are *premarket hours* from 4:00 am to 9:29 am and *aftermarket hours* from 4:00 pm to 7:59 pm. Trading activities also occur during both premarket and aftermarket hours, although the *volumes* (the number of shares traded during a period) are small (in other words, the market is not liquid).

Imagine a scenario in which Palantir Technologies Inc. (NYSE: PLTR) received a big contract and the news was announced at 8:00 am. This is the first moment to discuss. Not surprisingly, you will find that the stock price surged almost instantaneously at 8:00 am. At this moment, the people with whatever technology to get the news fast buy the stock and become the winners. On the other hand, the people who have a pre-set selling order at a certain price (i.e., a *limit order*) are too late to cancel the order and thus become the losers (defined due to their loss to the upside growth value) once their orders are filled. The trading decision of "buy" is a no-brainer at this moment. However, this opportunity is short-lived. Most people do not have technology that can inform them of the news instantly, nor do they have *insiders*' information about this contract that enables them to buy the stock before the price surge. When they realize the news, the price has already surged, and the opportunity has gone.

Now the time comes to 9:30 am—the second moment to discuss here. The market opens at 9:30 am. Liquidity comes in with millions of shares traded in this first minute. Who are the parties contributing to such volumes of traded stocks? Stockholders who see enough profits due to the prior price surge are selling their stocks. Opportunists who do not own the stock but anticipate the price may drop later are also selling (i.e., *shorting* the stock) by borrowing the stock from their brokers. The sellers are also called "*bears*," pushing the price down. In the meanwhile, bystanders who missed the prior surge are buying, hoping not to miss the second surge. The buyers are also called "*bulls*," driving the price up. In what direction does the price move? Theoretically, the odds are 50/50 up and down, depending on who wins the battle, the bears or the bulls.

Now the time comes to 9:31 am—our third moment to discuss. If the prior minute ended up with more bulls than bears, the price would go up, and vice versa. Let's say the price went up when the minute candlestick of 9:30 am closed on the chart. Then at 9:31 am, more bystanders may join the winning mass in buying because they see the buyers have won and can't wait to join the winners' party. The *short sellers* (i.e., the opportunists who do not own any stock but have sold their borrowed stock) are quite worried because the price is now against them and maybe against them even further. They have a strong desire to get out of their losing positions and start buying to pay back their brokers the stock they borrowed. If they do not, their loss can be huge because there is no limit on how high the price can go. They must buy back the stock they borrowed at whatever the market price is. This analysis reveals the two driving forces may result in a continuation of the upward trend. What are the odds of that? Let's say an experienced trader may expect 60/40 (60% up/40% down). This imbalance creates another "opportunity" that traders can take advantage of. Some trading books call it a "*1-minute breakout strategy*": After the market opens, the first minute's candlestick establishes a range. If the following minute's price breaks that range toward the north, buy; toward the south, (short) sell (Figure 1-1). This kind of "opportunity" does not require traders to possess any sophisticated tools or insiders' information to get notified instantaneously when the news is released. But it does require education, extensive experience, and skills which can tell that this is an "opportunity." How long does the "opportunity" last? Forever, as long as you believe this is an "opportunity!" Or never! You may have noticed I used quotation marks for this kind of opportunity, meaning it may not be real and may only exist in delusion for those who believe in it. If this is real, traders who know this trick just simply do it, do it, and do it, and they will be the winners who beat the stock market.

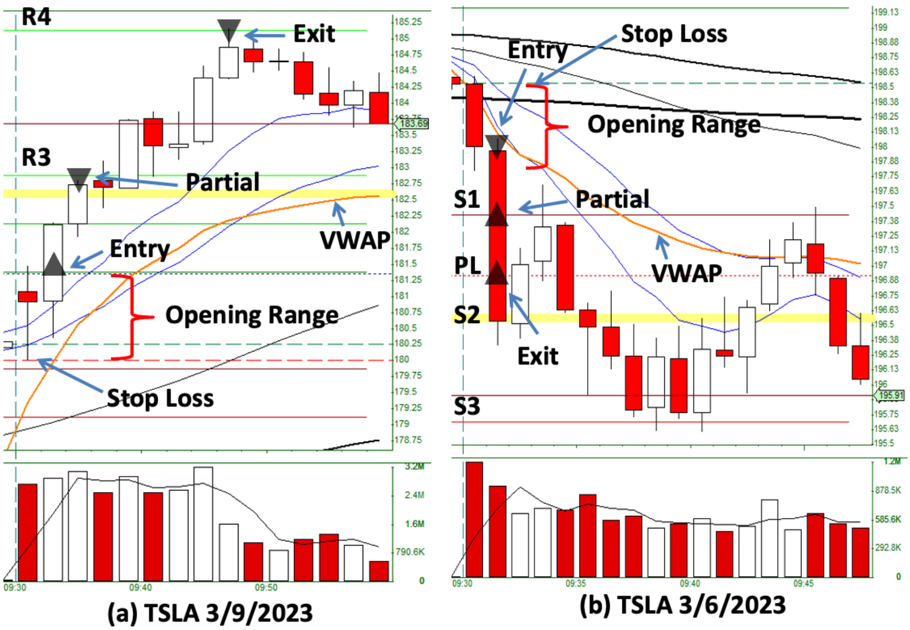
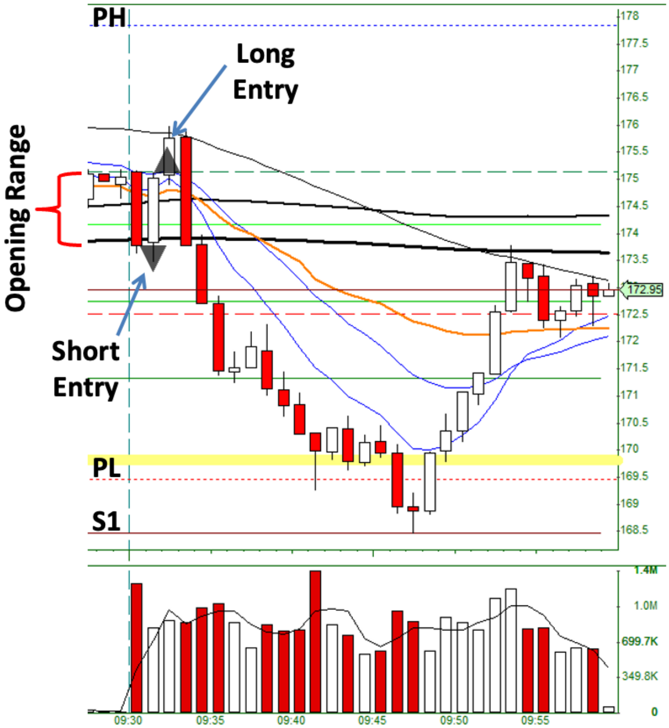


Figure 1-1. Sample successful applications of the 1-minute breakout strategy in (a) long and (b) short trades (Charts are on a 1-min time frame. PL denotes the premarket-low price. S1-3 and R3-4 denote the Camarilla pivot point levels.)

However, there are always traders who do not believe this "1-minute breakout strategy" and thus trade against it (Figure 1-2). The situation now becomes: If more people believe in the "1-minute breakout strategy" than people who do not believe in it, the strategy will work, and vice versa. How do we know if more people believe in it or not? The price history tells after the fact. Educating and inviting more traders to join in trading this strategy is helpful to make it work, or let a computer do the statistics calculations based on historical data to prove the odds are indeed imbalanced. Otherwise, it is still a 50/50 bet to most people.



Squeezed both ways trading TSLA 3/10/2023

Figure 1-2. Sample failed applications of the 1-minute breakout strategy regardless of going long or short (Chart is on a 1-min time frame. PH and PL denote the premarket high and low prices. S1 denotes the Camarilla pivot point S1 level.)

As you can tell, the financial markets are complicated and follow a random walk most of the time, except for those explicit short-lived highlights such as the news release moments that only insiders or well-informed people can benefit from. I have tried to code a bot to automatically scrape stock news from mainstream financial news websites and send notifications during live trading but ended up with little success because it was already too late when the news appeared on those websites. With a poor entry price, it’s easier to lose than to win. This is especially the case when human psychology kicks in. You may lose even bigger by holding a losing position longer due to a wrong belief! However, I do have coded algorithmic programs that can prove certain imbalanced odds like the “opportunity” in the third moment may exist in the stock market. It is also possible to use a computer to advise imbalanced odds based on statistics in scenarios like the second moment. That's what drives me to write this book to share the programs and the outcomes.

There are endless to introduce about the financial markets, as you can find tons of books discussing it from different perspectives. Here I am trying to restrain myself from straying away from the focus of the book during the introduction and instead, concentrate on building foundations to answer one question: How do financial markets benefit day traders? So far, the take-home message is that financial markets have hidden imbalanced odds as opportunities that are inexplicit to most people. As traders trade on delusional imbalanced odds but in fact are 50/50 odds, they end up losing. On the other hand, only a handful of traders trade on proven imbalanced odds and become successful. Therefore, our goal is to find the proven imbalanced odds that are implicit.

1.2 Day Trading vs. Swing Trading vs. Investing

Explicit opportunities such as positive news releases, as discussed in the previous section's example, are not available to day traders. But *investors* can enjoy their full benefits. Investors have a totally different mindset than day traders. When investors buy a stock, they must firmly believe in its upward growth trajectory. Therefore, they won't miss any explicit opportunities and will enjoy the full ride with each price surge. Warren Buffett has this advice to investors:

> *"If you are not willing to own a stock for 10 years, do not even think about owning it for 10 minutes."*

The cons are that as the stock price plummets, they also suffer the most by "*bag holding*" the stock from very valuable to valuable, from valuable to somewhat valuable, and from somewhat valuable to worthless. Although they won't become losers before they sell anything, their money is trapped and the opportunity costs are that they can't use the money during the period for anything else that is important to them, such as paying for medical bills, emergencies, education, and so on. Well-educated investors need to investigate each company they plan to invest in in great depth, including reading its earnings reports, following its website for news updates, learning the competition environment of its business, and so on. It is like investors are trying to build a marriage relationship with the company and want to know everything about the company beforehand. Once the relationship is established, divorce (selling the stock) is not a common option. Investors often look for target annual returns of 10% or so, which beats the inflation and market interest rate. They should not be influenced by short-term price fluctuations, and we say they should have a "*diamond hand*" on their holdings.

In contrast to investors, *swing traders* do not marry the company. Although they also do their *due diligence* by investigating the companies for the stocks they plan to buy and hold for a few days or weeks, swing traders have a clear and strict exit plan based on the technical data. If things do not work in the way they expect, they will sell the stock. Do swing traders enjoy the benefits of explicit opportunities like a positive news release? The answer is no, or at least it is not what they plan to do. Instead, when swing traders do their due diligence, they will figure out the dates when the earnings report will be released and avoid trading near those dates. Successful swing traders do not gamble on a positive earnings report or a negative one; they firmly trade based on their strategies. If there happens to be a news move in their favor, they will take it; if against their favor, they will stop out and take a loss. Note that their strategies are like day traders, exploiting proven imbalanced odds opportunities. The difference is their trading time window of days or weeks is much longer than that of day traders. This indicates that the methods introduced in this book may also be applied to swing trading for searching such imbalanced odds by computing the historical statistics with non-AI or AI models. Successful swing traders can achieve an annual return between 10-25%, which is higher than the commonly expected return of investors. However, it requires a greater devotion of time and education, and the "diamond hand" is not a quality anymore. Swing traders need to know where to stop out of their positions before they get into a trade and firmly execute the stop-out plan once the stop-out price is triggered.

Day trading is considered the most difficult trading activity of the three. As a result, the *Financial Industry Regulatory Authority* (*FINRA*) in the U.S. applies restrictions on day trading to protect people from losses. Such restrictions include a minimum of $25,000 worth of equity in your account, and your brokers will be required to label you as a *pattern day trader* (*PDT*) in their systems if they detect you have made four or more trades on the same ticker in any five business-day period so they can suspend your trades if you no longer satisfy the minimum equity requirement at any market condition. It appears hard to interpret such a restriction as a protection. In fact, it is a protection in that it causes you to rethink what you are doing by understanding the market more. For novice traders, day trading sounds like the easiest of the three, and they will dive in without sufficient education and end up losing big. Although there are ways of bypassing the PDT rule, such as opening a trading account with non-U.S.-based brokers who are not regulated by FINRA, it is not recommended, as foreign brokers offer limited protection of the equity in your account.

Day traders can essentially trade any stock without knowing anything about the company behind the ticker symbol. They will trade anything that has a decent *volatility* (i.e., a large range of price fluctuations) which they can benefit from by holding the stock for a very short period—from a few seconds to a maximum of one day. Absolutely, they will not hold the securities overnight; otherwise, they become swing traders, who apply a completely different series of strategies. Due to these features, we can clearly see that day traders do not marry companies either. They are trying to be free of any bias toward a company they are trading. Even if they are aware that a company released some good news before the market opened, which obviously may attract more buyers to drive the price up, they will still short the stock if their pattern-reading strategies tell them to do so. As discussed earlier, day traders will not benefit from the explicit opportunities like investors do, but since they always cash out by the market close, they will enjoy a good sleep every night without worrying about anything crazy happening overnight. In addition, successful day traders are usually looking for a target daily return of 2% of their account size by risking 1%. Since there are about 252 trading days in a year, that will add up to a target annual return of approximately 500%. That is a huge profit compared to investing and swing trading! No wonder it triggers a lot of people to jump into day trading and gambling, and at least 90% of them end up losing miserably.

Successful day traders are not gamblers, however. They are well-trained in three aspects: discipline, technical reading, and psychology. It is an important quality of a day trader to be okay with leaving a lot of money on the table and only trading the opportunities documented in their trade books. It sounds easy but is extremely difficult in practice. Greed is human nature. Since we are humans, not God, we are subject to it. The training of day traders mostly trains our discipline and psychology. We need to be extremely disciplined and psychologically stable to be good day traders. See? This is where computers can come in to help discretionary day traders because computers have the exact qualities of what is needed here. As trading rules are hard-coded into the computer programs, the computer will pop up a trading decision only when all criteria are met. There is no ambiguity in whether a trading rule needs to be followed this time or next time, it must be followed 100% of the time. For non-automated algorithmic trading, human traders behind computers still need to overcome the influence of psychology in the execution of such trading decisions suggested by computers, which is the hardest part. Without a trading model's assistance given the circumstance of a discretionary day trader, emotion control during trading is the biggest hurdle to overcome. Therefore, it is crucial to understand psychology to be a successful trader.

1.3 Psychology

Trading has drawn knowledge from many disciplines, and it would be an understatement if psychology is not classified as the most important one. Experiences from both successful and unsuccessful traders have proved that the technical aspects of trading are the easiest to learn and practice, while the psychological parts are the hardest. Since we are humans, we must admit we all have weaknesses that cannot be avoided. Note that the weaknesses apply also to all trading activities, regardless of whether it is investing, swing trading, or day trading.

Fear is the first human weakness to discuss here that is extremely harmful to trading. When the stock price goes against a trader, the trader tends to get out of the position due to the fear of losing more money. It could take hours to build up the price but only minutes to plummet. Why is that? Fear is the reason. When the price is on its upward trajectory following a big drop, it goes up very slowly because people are afraid of losing after they have seen the previous big drop and are thus hesitant to buy. On the other hand, a drop following an extended period of rising often turns into a plummet because people are afraid that a big drop is near the corner, and they start to sell, and the selling-induced pressure triggers more traders to become sellers. Thus, fear can "*paralyze*" traders to not get into any trades. The traders waited, waited, and waited. They watch the prices go up and down and curse themselves for missing out on so many good opportunities. Fear can also drive traders out of a trade when the price direction turns out to be in their favor in the long run of their trading time window. So, no matter which direction the price goes, the traders simply lose both ways.

Greed is another human weakness that is extremely harmful to trading. When the stock price surges, demonstrating a continuing trend in its early stage, it is very hard for traders who are closely watching the price actions not to jump into that trade. It is greed—a human nature that beats rationality. In most cases, if we jump into a trade like this on a prompt gut feeling, we end up losing. Why? Our prompt gut feeling is telling us it is free money, and it is an easy win by simply following the trend. In the meanwhile, our rationality is telling us there is no free lunch and at every moment the odds are 50/50 unless it is a documented opportunity of imbalanced odds in our trade book. The voice of rationality is usually very weak for novice traders, and greed takes over. Another common form of greed appears after we have made a winning trade. We may not be satisfied with the measly dollar amount of the win and want to win more. So, greed entices us to a trade in a not-so-perfect setup, and we lose part or all of our previous gains or maybe even more.

Such an unfortunate result easily triggers *anger*, which is the third human weakness that is detrimental to trading. It is natural and pleasant human nature to take the wins, but it is very difficult and reluctant to accept the losses. Rationality tells us not to take losses personally, as loss is quite normal in trading. Statistically, each trade is independent. The first losing trade does not increase the winning chance of the second trade, and we should simply strictly follow the strategies and rules. However, in practice, when our hard-earned money is punted by a bad trade, anger will strike us. Those well-planned strategies and rules are likely thrown out the window at that moment and we may start trading revengefully. Normally if we count each full entry and full exit as one trade, the number of daily trades for successful discretionary day traders is no more than two. If our trades are substantially higher than that number, we obviously have overtraded, either due to anger-induced revenge trading or greed-induced overtrading.

Hope is generally not considered a human weakness but a plus in many non-trading domains since it makes people optimistic during adverse conditions, which drives most of the potential out of humans to overcome obstacles they may encounter in life. However, it is an absolute weakness when it comes to trading, especially when we are trapped in a bad trade. Imagine we have a position of a stock and the price action is against us; if the price triggers our original exit plan (a pre-determined stop-out price), we should get out of the position immediately, regardless of what. The worst thing to do in this case is to change our exit plan and hold tight on that by increasing the stop-loss with the hope that the price will come back in our favor. There may be lucky times when the price does come back in our favor, but if the price does not come back this one time, you will lose miserably. If it happens a few more times, we will never make back the losses.

Regret is a strong feeling that strikes us when good opportunities are missed, and we believe we shouldn't let it happen for any reason. A well-trained trader is okay with leaving a lot of money on the table every day if it is not his or her setup. Novice traders, however, may be heavily influenced by the regretful emotion when they miss a long-awaited opportunity, making them less patient and unable to make rational decisions in subsequent trades and eventually end up losing big.

There are more emotions than the five listed above that are considered harmful for traders. For example, during trading, I like to hide the *P&L* (profit and loss) column on my trading platform because the joy or disappointment when I see the positive or negative dollar amounts may influence my psychology and rationality. Basically, as day traders, we need to control our emotions so that we focus only on the technical aspects of trading.

It is important to note there are also psychology-based trading strategies other than purely technical aspects based on charts of historical data. Such strategies work very well in that they are not based on statistics, but rather scientific facts. Migratory birds such as geese who migrate or travel long distances are well known for their formation of a V shape, i.e., the *echelon formation*. Although each goose's location is unpredictable, the feature of locations for a whole group is quite explicit. Given this knowledge, if we know the location of one goose, we can estimate the relative location of other geese pretty much accurately. This analogy can be applied to trading in that we can use the psychology knowledge—the scientific facts as a tool in our favor. For example, since we know the stock price goes up and down randomly, it is unlikely that it will go in only one direction forever. If it significantly drops for three consecutive minutes, a price bounce may be around the corner because many other traders are expecting the same thing and start to buy when they see the pattern, which is the psychological basis of the trade. We can therefore develop quick *scalping* strategies exploiting such knowledge. Scalping means you hold the position in a very short period, as you are not recommended to fight the decreasing trend established in this scenario. Do not be greedy. Another example of a psychology-based strategy is to trade against the common textbook-style strategies. That is, do not get into any obvious textbook-style trades (such as 1-minute breakout, double-bottom, etc.), but watch closely for the price actions. If the textbook-style trade works, you miss the opportunity and move on. If the textbook-style trade does not work, as you feel the price action is not right, you can go ahead to trade against it because the people who traded the textbook-style strategy will soon freak out and stop out by taking a loss, pushing the price in your favor. The price move driven by positive news is also explainable by mass psychology, despite that we, as day traders, just cannot exploit it in our favor due to the limits of our trading time window and rules.

Psychology, as one leg of a stool for day trading, has a lot to discuss. But since this chapter is about the fundamentals, I will not discuss it beyond these basics here. Let's now dive into the models and algorithms that build the foundations of trading with AI.

1.4 Modeling and Algorithms

When we see successful traders consistently win in buying low and selling high, we normally attribute that to experience. However, it is important to note that experiences are also models, essentially. These successful traders have all kinds of mental models in their brains. Why? Let's look at the definition of modeling. *Mathematical modeling* is the process of creating a mathematical representation of a real-world scenario to make a prediction or provide insight. This is exactly what human minds are doing every day to gain experience. Imagine how we learn to catch a frisbee. Whenever we see a flying frisbee, we see its historical locations through its flying path (Figure 1-3). With sufficient amounts of frisbee flying paths experienced, we have built and trained a frisbee-catching model in our minds based on intuitive physics. When we see a flying frisbee, our mind will automatically pull out the model, feed the model with historical data of frisbee locations, and the model returns the projected location of the frisbee in the near future so we know where to reach our hand ahead of time to catch it.

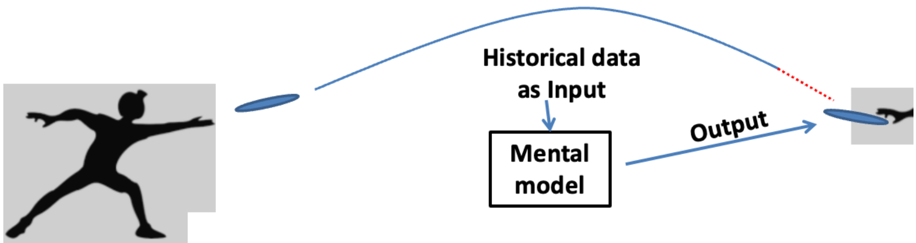


Figure 1-3. Illustration of a mental model catching a flying frisbee based on intuitive physics

The analogy is the same for stock trading. When we see for the first time a stock price approach the highest of the day, we don't know what will happen to the price next. But when we see the price eventually break the level and make a new high, we deposit a data point in our minds that under this market condition, the price will break the highest of the day. The next day we see another stock price do the same thing: approach the highest of the day and break it, so we deposit a second data point. And we see it appear for the third time, and so on. A mental model is being built, which establishes a correlation between a specific pattern and "yes or no" on "*highest-of-the-day breakout*." Now it comes to real trading. When we see the price approach the highest of the day, our mind pulls out the model and feeds it with the new data of the pattern. The model then outputs a "yes" or "no" on whether the price will break the highest of the day.

You probably see a problem here. The model development heavily depends on the data. In this case, the data are our experiences. If we have never seen a failed case of "highest-of-the-day breakout," our mental model will always give us a positive output, because those positive historical data are what the mental model was developed upon. It is therefore important to note that how good a model is depends on how good our data are. We will certainly experience a failed case someday because no strategy works 100% of the time in the financial markets. That's determined by the dynamic features of the markets. That failed case will impact the model's confidence level in the output. Previously, the model was 100% sure, now it may be 80% sure. Given more historical data, the model may be 50% sure or less, and then the "highest-of-the-day breakout" is no longer a tradable opportunity based on the model's output. This explains the learning curve of day traders. Novice traders are usually brave in jumping into a trade because they have not deposited enough data points and their mental model assures them a 100% probability of success. Many of them, therefore, have "*beginner's luck*," which means they win not because of their skills but rather their ignorance of risk. Once they have experienced one failure that made them lose big and caused emotional pain, they will change their behaviors from brave to conservative because their mental model no longer gives them predictions with 100% probability. Then what probability is given? Theoretically, if our experience on the "highest-of-the-day breakout" contained 4 successes and 1 failure, our mental model should give a prediction of success with an 80% probability when the setup shows up again and the strategy should be traded. The problem is, when it comes to real practice, the math is not that simple. Not all of us have a good memory. I know a friend of mine has a very good memory when she plays poker cards. Four of us played poker around a table using two decks of cards—108 cards total. During playing, she memorized all the cards that had been discarded from each of us, based on which, she optimized her strategies and always won. Is memorizing cards hard? Maybe not. I believe this may be an essential skill for those visitors to play casino games in Las Vegas. At least, for poker card games, those static data are easy to memorize. For example, there are only 4 colors and 13 cards in each color. Trading is hard in that your "experience cards" have no length limit and are constantly changing colors. Yesterday, the probability of success in the "high-of-the-day breakout" strategy was 80% with 4 wins and 1 loss as historical data. Today, with one more success point, the probability becomes 83% with 5 wins and 1 loss. Tomorrow, with one more loss, the probability becomes 71% with 5 wins and 2 losses. Are you able to memorize these probability data and track how many wins and losses you have for each strategy so your mental model can calculate the probability on the fly in a highly stressful trading environment? Probably not. In fact, since we are humans and we are emotional, with 4 consecutive wins followed by one single big loss, that emotional pain would make us ignore the fact that the success probability is still 80%, which is high in our favor. Instead, we might be "paralyzed" into not wanting to execute the trade anymore because that single loss was so painful. Or we might irrationally decide to trade against the strategy just because we have seen one failure case that caused us to lose big. We can see from these examples that trading based on our mental model has drawbacks. In summary, (1) our mental model is not trained by sufficient experience data; (2) it is hard to memorize our experience data and compute the dynamic probability for each strategy on the fly; and (3) it is hard for us to trade free of emotions. Therefore, we must refer to models independent of our minds.

How can we develop such models? Generally speaking, models can be classified into two categories: explicitly programmed and inexplicitly programmed. *Explicitly programmed models* are easily explainable because we know their working principles, the logic behind each inference in a process flow diagram, and the structure and data feed of those models. Recall the example of frisbee catching. We can develop a mathematical model based on the principles of physics. Given the initial height of the frisbee, an initial linear velocity, an angle of the linear velocity vector, an initial angular velocity about its rotation, the gravitational constant, the mass of the frisbee, and the buoyancy force as a result of fluid dynamics, a parabola-like formula can be derived to determine the projected position of the frisbee at any time. That formula is an explicitly programmed model. We know everything about it: how it works, why it works, and why it sometimes does not work. You may be wondering why there are scenarios where such a model does not work. Isn't physics an accurate science? It is if we include all factors into consideration. If that's our goal, we need to make this model more complicated. For example, we need to include the direction and magnitude of wind, the temperature and pressure of the atmosphere (which affects the *viscosity* of air), and even the longitude and latitude of the frisbee (which affect the *Coriolis effect* due to the rotation of the earth). If we include all factors, then all variabilities of a model's output will be addressed. Since we may not want to or be able to incorporate all factors into our model to make it perfect due to the difficulty acquiring the data of those additional factors or the inaccuracy in measuring those additional factors, it is not surprising that the model's prediction will not exactly align with the real frisbee's position. However, as long as we feel the result is good enough (a subjective judgment), the model can be deployed in the real world. How can we develop such an explicitly programmed model and apply it to trading? An example would be the "1-minute breakout" strategy in day trading. Factors that would influence the success of this strategy and are thus included in the modeling process could be premarket trading volumes, *VWAP* (*volume-weighted average price*), premarket-high price, premarket-low price, type of driven news (positive or negative), *market cap* of a company (low float or high float), weekday, premarket price actions, and so on. For simplicity, let's use a linear model. A weight is given to each of these factors in the model. As mentioned earlier, such a model is easily explainable. A positive weight means a positive contribution from that factor to the outcome. The greater the value, the greater the contribution. Similarly, a negative weight means a negative contribution from that factor, and a weight of zero means no contribution. The weight values are adjusted to best fit whatever data are used. The modeling is as simple as that. When it then comes to real trading, a computer automatically reads the data of premarket trading volumes, VWAP, and all other factors, and feeds them into the model to compute the outcome, which is displayed on the screen as "break-out" or "no break-out." Probability values are given as well with these predictions, based on which you can trade accordingly. Cool! But how reliable is the model? Is it as good as the frisbee-catching model in terms of accuracy? Like the frisbee catching model, if we can include all factors in this model, then the output should be 100% accurate, theoretically. However, since we can't include all factors, there will undoubtedly be unaddressed variances between the predictions and the actual outcomes. In addition, the factors we included in the modeling process are arbitrary: Some are real factors, while others may be fake factors. That is why a good algorithm is very important because it can get rid of the negative impacts of the inclusion of fake factors on a model's output. The bottom line is explicitly programmed model provides a sense of security to traders. In order to get peace of mind, investors do their due diligence to understand everything they can about a company before they put their money into the company's stock. If we decide to use models for day trading, we also need to do our due diligence and understand the model as best as we can to have peace of mind. Explicitly programmed models do very well here because it does not require a genius to completely understand them.

Implicitly programmed models are primarily data-driven AI models. We will see in later chapters of this book how *artificial neural network* (*ANN*) models or other deep learning models are developed to aid day trading. Those models are examples of inexplicitly programmed models, where several lines of codes create millions of "neurons" arranged in multiple connected layers and each "neuron" has a weight like the simple linear model in the previous example. Since the choices of how many "neurons" to use and what structure to arrange these "neurons" are arbitrary, there is no way to interpret their physical meanings, but they do work very well. In recent years, the phrase "*deep learning*" (*DL*) has gradually replaced the phrase "*neural network*." Since the neural network field had become tranquil for a long time without any significant breakthroughs prior to 2012, creating this new terminology was a marketing strategy to attract more active research into the "neural network" field. "Deep learning" is indeed a better name than "neural network" anyway because the current ANN structures do not resemble the real neural network of our brains in that the neurons in our brains are interconnected, but the neurons in ANN structures are only forward-connected between two adjacent layers (Figure 1-4).

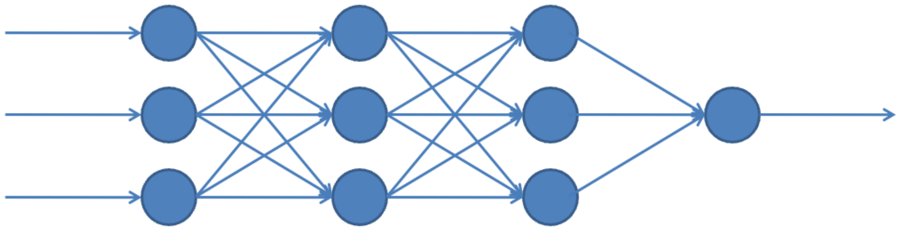


Figure 1-4. Illustration of an ANN structure that is forward-connected between adjacent layers

In contrast to DL, is there shallow learning which is also data-driven AI? Yes, data-driven shallow learning AI is usually called "*machine learning*" (*ML*). I also consider this as a marketing game to attract more research. "*Statistical learning*" should be a more appropriate name. Many data science professionals would also call it this way because it essentially draws extensive knowledge from statistics and many other advanced mathematics if we completely understand its algorithms. "Machine learning" gives the impression of a black box, which makes people feel it is okay to not understand what is under the hood. Just let the machine do its job! We will develop ML models for trading in the chapter right before the development of DL models. Note that we cannot say DL is better than "shallow level" ML or the other way around. Whichever works for you is the best and it could be a very subjective judgment, regardless of the model evaluation metrics. I know financial companies use shallow-level linear regression ML models to capture credit card fraud because such models are easily explainable and work quite well. I also see some algorithmic traders advocate that *support vector machines* (*SVM*, a type of ML model) gave them better results after they tried multiple data-driven AI models. We will keep the question of "Which model is the best" open for now. In later chapters, we will learn how to keep the best of a pool of different models using a voting mechanism.

Now let's look at the *algorithm*, a word that is daunting to many non-math majors. Algorithms for sure require a lot of math knowledge to be understood. The output of an algorithm is a model. The relationship between models and algorithms is similar to that between cars and auto mechanics. Auto mechanics lay the scientific foundation for the production of a working car. But do you need to be an auto mechanic to drive the car? No, driving a car requires a different set of knowledge, which is not as specialized as that of auto mechanics and is relatively easy. That's why almost anyone can obtain a driver's license. What about a driver with a knowledge of auto mechanics? In order to become an auto mechanic, specialized training is necessary to be qualified. However, that does not mean a driver cannot self-study some auto mechanics knowledge and be very handy in doing some simple regular maintenance or solving common car problems such as jump-starting or replacing the car battery, changing a flat tire, refilling windshield wiper fluid, checking engine oil level, and so on. Here is the analogy: If you would like to be a handy person during the deployment of your trading models, learning some algorithms would be helpful! Model development is easy—just several lines of code. It is like driving—almost anyone can do it, of course after you finish reading this book. The scientific foundation of a model is the algorithm, which you do not have to know. If you do know some basic principles of algorithms, then you will excel in gaining peace of mind when using the trading model because if the model does not work the way you want, you won't panic. Wouldn't that be the same feeling when a handy driver, not a driver who cannot change a flat tire, is on a long road trip in the middle of nowhere?

With that said, let's briefly dive into algorithms. There are *AI algorithms* and *non-AI algorithms*. AI algorithms can be classified into regression algorithms and classification algorithms, while conventional non-AI algorithms lead to two types of models, either theoretical or empirical. In the dynamic financial markets, theoretical models are useful in interpreting textbook-style finance phenomena scientifically, such as the bond yield vs. stock return relationship (As bond yield increases, the stock price goes down, and vice versa) and the stock value vs. dividend relationship (stock value per share equals dividend per share divided by the difference between interest rate and company's growth rate). It is considered scientific because numerous research papers have proven it and mainstream academia accepts it. They are generally not considered very useful in swing or day trading because hardly any trading decisions can be derived out of them. Investors may find them valuable since their holding period of securities is long enough for them to experience the values revealed by such theoretical models. Beyond the theoretical models in textbooks, traders may come up with a variety of empirical models based on algorithms that are not fully explainable or understood by scientific fields but may still work well. For example, profitable day traders are good at reading patterns of price charts. Once a specific pattern appears, the stock price is likely to move in one direction. An algorithm that portrays the correlation between the price pattern and the price direction leads to an empirical model because it is based on experience and is thus scientifically unprovable. Day traders and swing traders would love these models because they are intuitive to learn and closely resemble their mental models.

With regard to the two classes of AI algorithms—*regression* and *classification*, both are quite useful in trading. A regression example would be a scenario where we want to know the lowest or highest price that a stock can go to within a specific time window. The output of regression is continuous data. For this case, the lowest or highest price of the model's output must have two decimal places to be considered useful. Let's say, within a 5-min time window, a stock may fluctuate between $10.10 and $10.30 per share given its recent price actions. That means there is a $0.20 fluctuation range that can be exploited by day traders. If the model can give us a prediction of $10.29 as the highest and $10.11 as the lowest, guess what? The trading decision is clear: (1) Short sell the stock as the price approaches $10.29 and cover the position when the price hits $10.11; or (2) *Long* (means buy) the stock as the price approaches $10.11 and sell when the price hits $10.29. Such a model is a regression model because it gives us results in decimals and we could get continuous output such as $10.11, $10.12, $10.13, $10.14, and so on if the model's input data changes in a certain way. A classification example would be an answer to the stock price's general direction, as we only have three classes in this case: flat, up, and down, which may be correspondingly labeled as 0, 1, and 2 in our code. Sometimes we may only want to know whether the stock price will go up. Then, there are only two classes: not up and up, which may be labeled as 0 (means negative) and 1 (means positive) in our code. We can name numerous other classification scenarios for our trading needs. In such scenarios, the model outputs discrete values, not continuous values like the regression example. So, if we try to answer any type of "yes-or-no" question or "multiple categories" question, classification algorithms should be used. Conversely, if we try to obtain a prediction with a continuous quantity, we should use regression algorithms.

There are also numerous algorithms within regression and classification that we may pick for our trading model development. As shown in Figure 1-5, the x_1 axis is the percent of the price above VWAP and the x_2 axis is the *market cap* (outstanding shares multiplied by stock price) of a company in billions. The imaginary data are marked in either a circle or a cross in the figure, meaning trends are kept or not kept, respectively, within a certain time window. The logic behind the implied algorithm is as follows:

We believe by experience that VWAP and market cap are two factors that determine whether the relative position between the stock price and VWAP can hold. If a stock is traded at a price below VWAP, this means the stock is weak and likely to remain below VWAP within a certain time window. Thus, a decreasing trend is kept. Conversely, if a stock is traded at a price above VWAP, this means the stock is strong and likely to remain above VWAP. So, an increasing trend is kept. If such a "theorem" does not hold, let's attribute it to the market cap of the company because low market cap (also called *low-float*) stocks are easily manipulated by market makers since they need less money to move the stock price.

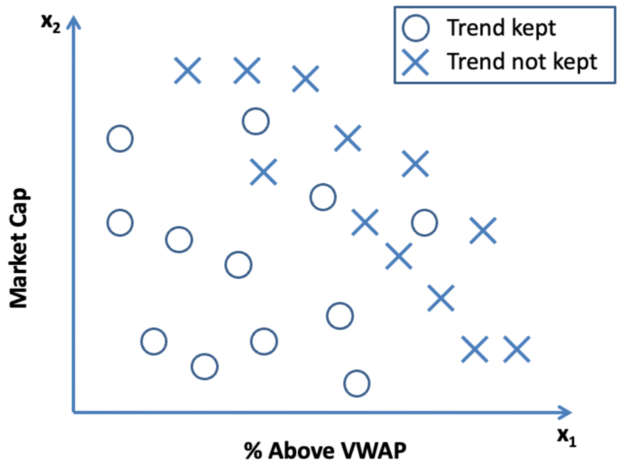


Figure 1-5. A sample demonstration of a classification problem of "trend kept or not kept" based on the inputs of VWAP and market cap

By plotting the circle or cross data points in the figure, it becomes intuitive that we could draw a line to separate crosses from circles as our trading model's decision boundary. The performance of the trading model largely depends on how well that line is drawn (Figure 1-6).

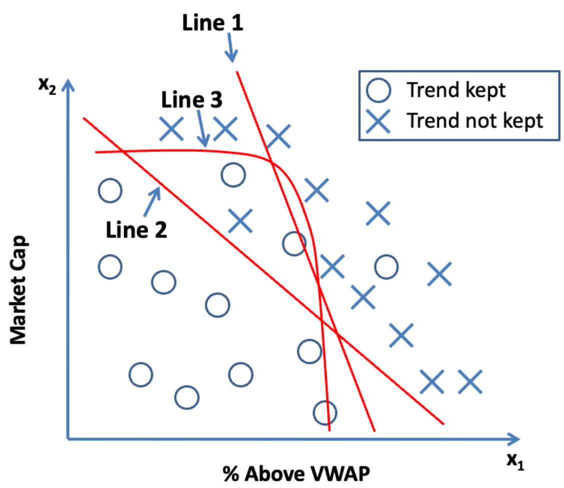


Figure 1-6. Three lines as decision boundaries of three models for the demo classification problem

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Shunyu Tang

Day Trade With AI

Highlights

- A book where finance theory meets data science
- Sound strategies supported by the efficient market theory and behavioral finance
- Minimum math for a clear explanation of machine learning and deep learning algorithms for trading
- Reusable code snippets for easy deployment in algorithmic trading
- A comprehensive hands-on guide to making AI your personal assistant to trading

"Quite ingenious and insightful, and whereas your thoughts, perception and intuition are in precisely the correction market analysis dimension and direction...and as a former NYSE Market Maker this is the Master Key to absolute precision and laser accurate trade targeting and timing of trade executions..."

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"Great article, creative feature engineering. I was looking at something like this too a little while ago and this has motivated me to try it again a little differently."

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Shunyu Tang is a computer science enthusiast who strives to make day trading a solid science founded on the interdisciplinary fields of finance and data science. As a technical writer and quant trader, he is ranked by Medium as a top writer in Finance and Algorithmic Trading. He is also the editor of a Medium publication, *AI Advances*, which publishes advances in AI and its applications in all facets of modern society.

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