Buy the DIP

AI-Driven, Actively Managed

Active Exchange Traded Funds were going to revolutionize the ETF world, but so far they have not. One possible reason: most active ETFs aren't all that active. The portfolios remain relatively static over time and as a result, the funds may surrender the biggest supposed advantage of active management – the ability to adapt opportunistically to changing market conditions.

Of course, trading for its own sake is not particularly useful and can drive up costs. Further, active management is not appropriate for all strategies. But there clearly are circumstances where an active manager can add value. We believe one of those is "buy the dip" (BTD) – an investment strategy that seeks to take advantage of a temporary dislocation in the price of a stock that otherwise should be trending higher – that seeks to buy at the bottom of the selling trend and then sell at or close to the end of the rally. When properly executed, it can be a useful tool for contributing alpha to a portfolio.

Exploiting this potential pricing inefficiency is not easy. Doing it consistently requires a massive amount of data and research, as well as a certain risk tolerance. Intuition alone is not enough. To be successful, the investor must assess the reason for the pressure on the price of the shares, and make a determination – does this represent an idiosyncratic, short-term movement in the stock or something more fundamental, the first leg down as part of a longer-term negative trend?

In other words, is it a "dip" or a "dive"?

Also important is trade execution – how to optimize the buying and selling to maximize return. Making money can mean consistently solving for these issues and doing so in nanoseconds.

This generally is considered beyond the capabilities of even the most talented human traders. But that doesn't mean it can't be done. The application of artificial intelligence (AI) to the investment process is one potential solution.

Evolving applications

Over the past decade, AI has evolved from an intellectual curiosity to a powerful tool for analyzing and identifying patterns in data that would otherwise escape the attention of human observers. Using principles drawn from mathematics and physics, among other disciplines, it is now applied broadly across the economic landscape. One of the most prominent applications is fraud detection. This perennial challenge for banks and other financial services providers is to offer the conveniences demanded by consumers (i.e. mobile banking, instantaneous fund transfers), while ensuring the necessary security.

Billions of transactions run across the global financial system every day, creating a huge opportunity for illicit behaviors. A study by the credit reporting agency TransUnion found that online fraud attempt rates for financial services rose by **149% between Q4 2020 and Q1 2021** alone (even though the former period includes the holiday season). Another firm, Javelin Research, estimated that banks lost as much as $56 billion to fraud in 2020, an **83% increase** over the prior year.

The growing sophistication of fraudsters and increasing frequency of attacks have quickly scaled the problem beyond the capacity of risk management departments to oversee. Recognizing this, financial institutions have increasingly deployed AI to address the problem. With its massive data-crunching ability – and its facility at pattern recognition, AI offers a potential compelling solution to the fraud problem. Hundreds of thousands of transactions are continually analyzed and neural networks are used to assist in flagging anomalies to help banks and other financial institutions strike that balance between security and convenience.

This is one of many powerful use cases now emerging for the practical application of AI technologies.

Using AI to understand factor relationships in stocks

For an ETF, the analogue to security and convenience is risk and return; you want to generate the appropriate amount of return for each unit of risk you assume. AI allows for a more rigorous application of this principle. A two-part challenge exists in solving for Buy the Dip: first, determining whether there is an identifiable set of factors that can be used to reliably separate “dips” from “dives”; and second (assuming the first question is answered in the affirmative), employing those factors in a timely enough fashion to generate positive returns.

Our research has identified more than 25 factors that are historically correlated with a true dip. Many of these are derived from analysis of underlying drivers as well as anomalies in trading volume and price movements, using a wide variety of sophisticated statistical tools. But these factors do not operate independently; they exist as part of a complex ecosystem. The interrelationships are dynamic and change constantly depending on market conditions; factors that are strongly correlated under some conditions may be less correlated under others as the interdependencies adjust. Our view is that understanding these shifting relationships is the key to building successful predictive AI.

The ability to analyze and understand how these features interact with each other and influence share prices quickly scales beyond the capacity of any one analyst — or even team of analysts. As such, we believe a human-driven buy the dip strategy will always be limited, circumscribed by the ability of a trader or portfolio manager to identify possible trades, how long it takes to execute those trades, and the number of trades that can be executed in a given period of time.

It's here that the use of AI and machine learning can excel. AI can apply scientific methods to a volume of data on a scale that may be unfathomable to the individual analyst to optimize trading decisions for short-term gain. It can do this in nanoseconds, for thousands of securities, over and over again.

AI can potentially seek to identify dips, initiate the buys, and then instruct when to sell the rebounded shares, eliminating the guesswork in finding and timing these transactions.

Opening the black box

AI strategies have been criticized in the past for their opaqueness. Machine learning is turned loose on a set of equities to seek out profit patterns. Those patterns are then used as the basis for trading for reasons that are often obscure to their human overseers. Some of these strategies have demonstrated a level of utility; others have not. What has become increasingly clear, we believe, is that this blind "black box" approach to applying AI to a market is not sufficient to achieve reliable results.

A fundamentally sound application of an AI system requires setting constraints both in the design and in the use case. This initial instruction set – the kernel of "intelligence" – is imbued by its designers. As such, success may be dependent on the competency of the designers to architect an algorithm that is robust enough to manage different market scenarios. By definition, most but not all will fall within "normal" parameters, but the system needs to be sufficiently robust to address non-normative scenarios. In our view, the algorithms employed to do this should be thought of simply as a set of instructions, expressed mathematically.

The machines then learn based on these instructions, along with the market data provided to them and may quickly begin to potentially outperform humans in the repetitive tasks to which they are assigned.

This falls into an emerging category of portfolio construction known broadly as "scientific investing," a form of active management that is informed by data science and advanced statistical analysis. In the case of buying the dip, the goal is to leverage machine learning to exploit and identify market dynamics that lead to trade entry and exit signals, while maintaining full investment across the universe of designated securities.

The AI behind DIP isn't a single machine or model but rather is a collection of machine learning algorithms working independently and in coordination to track and qualify billions of data points. The collective AI then applies a proprietary set of filters to these qualifiers to identify and evaluate likely dips, with the most promising of these flagged for purchase.

A DIP ETF, the Practical Application of AI

These ideas find practical application in the BTD Capital Fund (Ticker: DIP), an exchange-traded fund which utilizes ongoing, and emerging, peer-reviewed AI research from academia and the financial industry in executing its buy the dip strategy. Each of these systems is trained on more than 15 years of intra-day market data and contributes to the generation of the entry and exit signals for potentially lucrative opportunities while simultaneously determining how to control and mitigate risk.

The AI system underlying the fund gathers data from multiple proprietary indicators for more than 1,000 large cap U.S. stocks, flagging behaviors or anomalies in intra-day trading patterns that it has determined typically precede dip events. It then generates buy signals for stocks it calculates are at the bottom of a dip and sell signals for those it determines have recovered their value and executes those trades.

The fund will generally hold anywhere from 20-40 stocks and is actively managed, with the portfolio turning over an average of 10% to 30% per day. The average holding period for any individual stock is two to seven trading days but can be longer. DIP is designed to outperform its S&P 500 benchmark over time, adding alpha through active management, while maintaining a significant correlation to the broad U.S. large cap market.

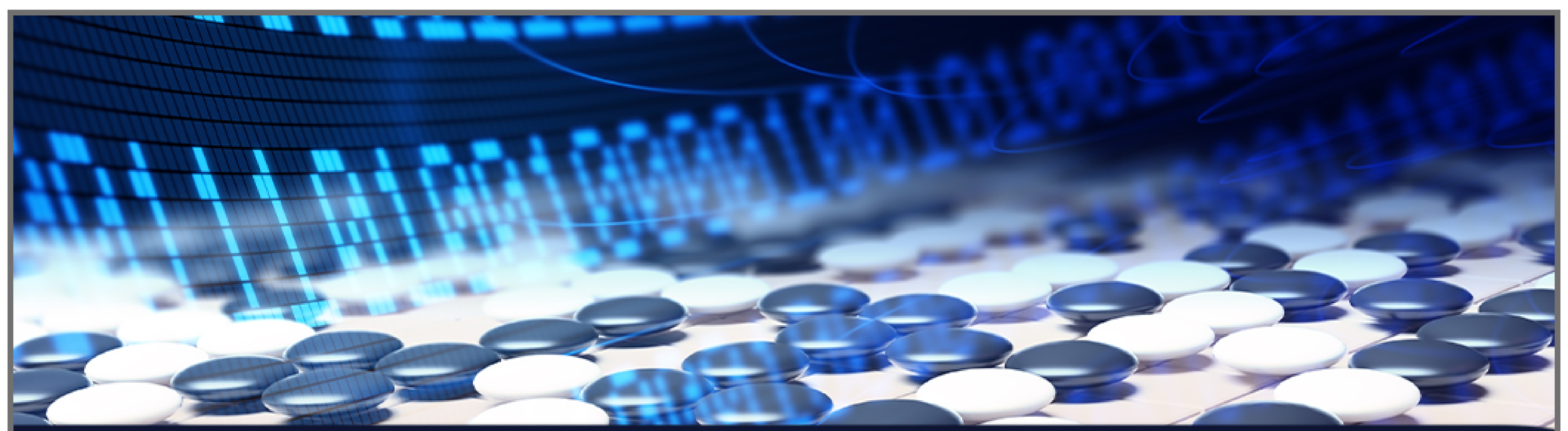
Utilizing traditional index-based ETFs to generate profit in a declining market presents challenges, but DIP was designed to operate efficiently in all market conditions.

In those instances where DIP's AI determines that fewer than 20 stocks are identifiably in a dip at a given time it will allocate excess capital to a bespoke portfolio of four U.S. broad market index-based ETFs as it continues to seek new opportunities. While there may be fewer opportunities in a downturn, DIP's AI was built with the goal of finding true dips in individual stocks, which can occur regardless of the overall market performance.

Buy low, sell higher, repeat

On its face, "buy the dip" appears to be a highly intuitive strategy. Unfortunately, experience has shown that intuition alone often leads investors astray. The DIP ETF brings scientific discipline to this process, combining reams of market data with state-of-the-art AI technology to identify and seek to capitalize on clear statistical patterns that predict a reversion to the mean – a short-term 'bounce' in the share price. Its machine learning-based technology powers an actively managed ETF, providing a new way of looking at one of the oldest market strategies – buy low, sell higher, repeat.

To explore this idea further,
visit our website: **www.kaiju.ai**



Reinventing a 3,000 year old board game

Go is a seemingly simple board game invented by the Chinese about 3,000 years ago. It is traditionally played with 181 black and 180 white "stones" on a square wooden board checkered by 19 vertical and 19 horizontal lines. Collectively, these form 361 intersections.

The purpose of the game is to occupy territory by enclosing empty spaces with stones placed on the intersections. From this relatively simply strategy there arises an astonishing 10 to the power of 170 possible board configurations – more than the number of atoms in the known universe. This makes the game of Go a googol times more complex than chess. (A googol is a "1" followed by 100 zeros.)

Around 2014 a Google (now Alphabet) offshoot called DeepMind Technology created an AI-driven computer program designed to compete for the world Go championship. Utilizing deep neural networks similar to those that power DIP's AI, AlphaGo was introduced to Go's rules and typical gameplay and then began to compete against some of the world's most elite Go players. In one match, AlphaGo made moves that were so unusual, so profoundly different from those that a human would play that its programmers believed it to be malfunctioning. But by leveraging patterns invisible to humans, AlphaGo won — upending hundreds of years of gameplay wisdom.

We believe the introduction of AlphaGo to the rules of the game is roughly analogous to how DIP's AI employs the set of factors correlated with a successful buy the dip strategy. It's a point of departure. As with AlphaGo, the AI goes deeper and faster into the analysis than any human could, potentially allowing it to identify and leverage patterns to achieve its goals.

AlphaGo brought a new way of seeing to a thousand-year-old-board game. DIP seeks to do the same with an investment strategy that is thought to be well understood but has yet to be fully optimized.

Disclosures:

Investors should consider the investment objectives, risks, charges and expenses carefully before investing. For a prospectus or summary prospectus with this and other information about the Fund, please call (800) 617-0004 or visit our website at www.kaiju.ai. Read the prospectus or summary prospectus carefully before investing.

The Fund is distributed by Quasar Distributors, LLC. Exchange Traded Concepts, LLC (the "Adviser") serves as the Fund's investment adviser.

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