Forms Shape Ideas

The Application of Pattern Search Technology in Finance

IFTA 2014





The Knowledge





Brain's 'Inner GPS'





The Knowledge





The Knowledge





Patterns Search in Big Data



Dr. Xiaoping Zhang, CEO and cofounder of EidoSearch



- Internationally renowned expert in information processing
- Developed algos for genome sequencing, EEG neural activity and NASA imaging





A Paradigm Shift in the Predictive Modeling of Big Data



- Models require too many assumptions
- Models are too rigid and limited in capability
- Models are becoming more and more complex
- Associative memory supplants the need for traditional models
 - Organized time series data **IS** the model for generating Predictive Analytics



The Approach



- Just as the human brain uses **associative memory**, we use prior experiences to predict outcomes
- Associative memory does not require rigid or simplifying assumptions the data (experiences) predicts the future







EidoSearch



Approach	Traditional Modeling	Associative Memory			
Input	Mass of the ball, initial velocity	Compare trajectory to similar trajectories			
Equation	Law of gravity, model of air resistance	Not necessary!			
Prediction	Point where the ball is predicted to land	Area where the ball landed after similar trajectories			

Paradigm Shift in Finance

- As models progress, explanations tend to become more and more complex a Paradigm Shift offers radical simplification
- As an example of increasing complexity in models, let's take a look at modeling volatility in finance



Traditional Modeling

- 1982: **ARCH** Assume the variance of the current error term to be a function of the actual sizes of the previous time periods' error terms
- 1993: **NGARCH** Reflects the leverage effect, signifying that negative returns increase future volatility by a larger amount than positive returns of the same magnitude
- 1995: **GARCH-M and QGARCH** Used to model symmetric effects of positive and negative shocks
- 2013: **fGARCH** Omnibus model that nests a variety of symmetric and asymmetric GARCH models



EidoSearch













EidoSearch



The Upper and Lower Bound projection lines show standard deviation of the up results and down results, respectively, in the next period.



Janus Capital Group (JNS)



• 62 similar instances in US Equities

EidoSearch

• Only 3 similar instances in Financial Services



Projected Range of Outcomes

• The stocks are down on average -8.5% over the next 1 month with more than 6x the downside to upside.

JNS Janus Capital Group, Inc.			-8.5% Avg. Return	4.4%	-28.9% % Downside	\bigcirc
85% probability the stock will be	< \$16.58 in a month.					
					~~~	17
				×		15.89
					~	14.54
						14
						13
~~~~	$\sim$	~~	~			12
	h	~	~		~~	1
						11.29

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Actual Outcome





Empirical Validation

Pattern	Forecast	Number of	% in	% in	% in	% in
Length	Length	Predictions	Bucket 1	Bucket 2	Bucket 3	Bucket 4
1 month	5 days	986,140	13.20%	37.30%	37.00%	12.50%
-						
3 months	1 month	960,623	13.60%	37.20%	37.30%	11.80%
6 months	3 months	931,333	14.60%	36.00%	38.50%	10.90%
6 months	6 months	894,728	15.70%	33.60%	39.40%	11.20%
9 months	6 months	900,443	15.70%	33.50%	39.60%	11.20%
		4,673,267	14.60%	35.50%	38.40%	11.50%



A New Approach

- Most models try to find some relationship that explains all of the examples. The best fitting model fits all of the data best.
- Content-based search allows for the possibility that not all the past data matters in a given situation
 - It's an empirical method
 - It allows us to capture complex relationships in a simpler way
 - Search by example is the foundation







Predicting Equity Returns



Is it Predictive?

 Within a liquid universe of the largest 1,000 U.S. equities, a market neutral strategy which goes long the highest-ranked decile of stocks and short the lowest-ranked decile of stocks produces annualized returns of 21% with a Sharpe ratio of 2.0





Our Axioms

- Financial time series data patterns, such as price patterns, reflect aggregate investor or system behavior in the market, including liquidity supply and demand and behavioral biases.
- Although the behavior of market participants and their responses to changes in market conditions and microstructure change over time, we should expect some consistency in their exhibited behavior
- This expectation underlies the idea of the predictive nature of trends in time series data, and that patterns should repeat over time.



Research Methodology

- We restricted our universe to large, investible names
- We constructed a time-varying universe of the 1000 largest U.S. equities by market capitalization, roughly analogous to the Russell 1000 index components
- The searches were performed across historical top-1000 names
- We divided our historical data period into three sections:
 - Search space period: 1990 to date in question (no look ahead bias)
 - In sample period: 2006 to 2009
 - Out of sample period: 2010 to 2013



Research Methodology

- We examined patterns designed to predict the next 5 trading days of a stock's returns
- We updated these signals on a daily basis, and evaluated them the next day
 - For example, if a signal was generated using close-to-close daily returns through Monday, we would act on the signal in our simulations from Tuesday's open price, and hold through Wednesday's open



Returns

EidoSearch

- Monotonic returns across the 10 decile groups
- Indicates the strategy's ability to differentiate between underperformers and outperformers, though the top and bottom decile certainly provided the most differentiation.





Cumulative Returns

- Next we construct long/short portfolios to examine the time series properties of a strategy based on our forecasts.
- On each day, we sort the stocks into equally sized quintiles (200 stocks each) based on our forecast.
- We then create an equally weighted long portfolio consisting of the stocks with the highest forecasts, and an equally weighted short portfolio consisting of the stocks with the lowest forecasts.
- We plot this market neutral portfolio's cumulative returns throughout our historical period, and do the same for decile portfolios (100 stocks each).





Returns

• We also show the annualized returns of the long/short portfolios, and their annualized Sharpe ratios.

Long/short annualized returns								
	Decile		Quintile					
	Return	Sharpe	Return	Sharpe				
Feb 2006-Jan 2014	21.0%	2.00	14.2%	1.89				
2006 from Feb	23.6%	3.41	17.7%	3.45				
2007	14.5%	2.46	8.2%	2.01				
2008	54.4%	2.53	35.2%	2.24				
2009	34.5%	2.40	23.8%	2.40				
2010	5.2%	0.98	6.7%	1.75				
2011	15.3%	2.17	7.6%	1.55				
2012	10.2%	2.15	6.3%	1.73				
2013	12.9%	2.81	9.5%	2.86				



Returns

- The strategy exhibits positive returns in every year, with particularly strong predictability through the global financial crisis in late 2008.
- Stock returns during that period were decidedly not fundamentally driven, and technical patterns which captured liquidity demands in the market were particularly predictive.
- Despite the extreme returns during this period, the Sharpe ratios of the strategy was only somewhat higher, reflecting the much higher volatility in the market at the time.



Reversal

- Could an investor achieve the same results by employing a simple strategy of buying past loser stocks and selling past winner stocks?
- We conducted several studies to verify that the returns to the EidoSearch strategy are not subsumed by the naïve reversal strategy
- The two strategies have a correlation of only 6% on average.
 - This makes sense given that the EidoSearch patterns are agnostic to the particular shape or trend and therefore don't find just a single predominant anomaly as does the reversal strategy.



Reversal

- Here we see that although losers strongly outperform winners as shown by the higher general values in the "Within Prior Losers" column, the EidoSearch strategy is also quite profitable within the prior loser and prior winner columns
- The lower rows outperforming the higher rows by 25.6% within the Prior Losers group and 17.5% in the Prior Winners group.

		Within	Within
Eidosearch		Prior	Prior
forecast:	Overall	Losers	Winners
Low	5.7%	14.0%	-9.1%
2	10.6%	18.0%	-1.3%
3	11.7%	23.4%	2.1%
4	12.4%	21.9%	3.3%
High	19.9%	39.6%	8.4%
High-Low	14.2%	25.6%	17.5%



The Associative Memory Approach



- Predict daily returns for 1,000 U.S. equities over the last 8 years and analyzed the result of buying the top 1% and shorting the bottom 1%
- The strategy would have yielded a *668%* cumulative return over the 8 year period.

📕 Quantopian							MY	ALGORITHMS	COMMUNI	TY HELP	· 川
Eido Signal - dynamic	universe						Currently	live trading	✓ All Backtests	Algorithm	Backtest
Settings: From 2007-02 Status: ✓ Backtest co	2-02 to 2014-05-19 omplete	with \$100,000 initial capi	ital (minute dat	a)				Live Trade A	lgorithm Q	Share Results	•
Results Overview	Total Returns	Benchmark Returns 50.6%	Alpha 0.88	Beta 0.21	Sharpe 3.15	Sortino	Information Ratio	Volatility 0.28	Max Drawdow 34.1%	vn	
Transaction Details	Cumulative perfo	ormance: 📕 Algorithm 668	3.04% Bench	1mark 50.67%				Week of M	May 11, 2014	Week Month	n All
Position Values								~	~		
Unrealized Gain/Loss							~~~~				500%
Log Output			m	~~~~							0%