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Deep Learning to Predict Regime Changes Using Constrained Time Delay and Recurrent Neural Networks

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Deep Learning & AI Conference: Table of Contents

Deep Learning to Predict Regime Changes

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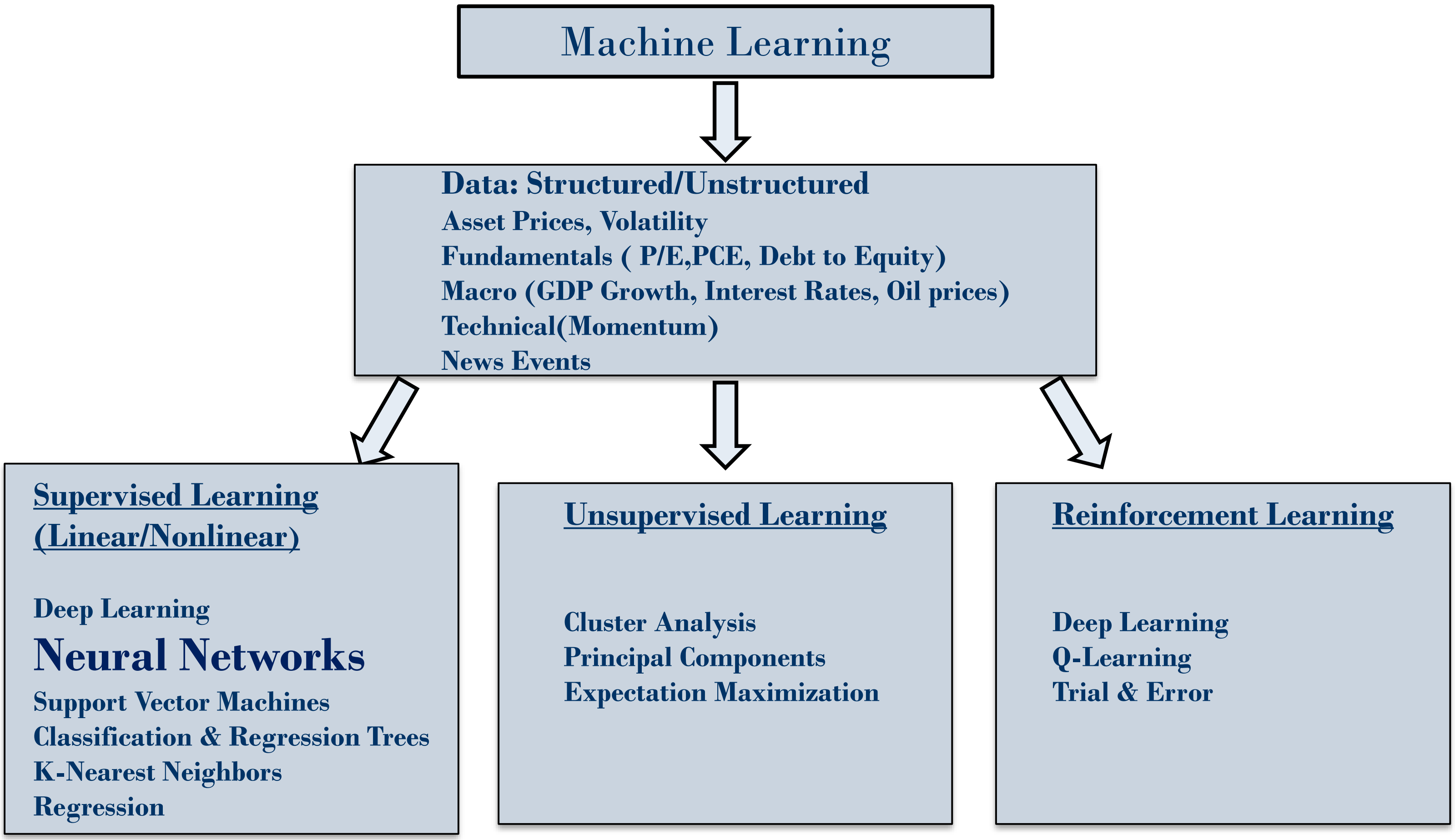
Deep Learning

- **Investment & Risk Management**
  - Forecast Volatility Regimes, Factor Trends, Economic Cycles
  - Big Data including Time Series Data, Interday, and Intraday
  - Neural Networks: Static vs Dynamic/ Black Box/Pattern Recognition
  - Ensemble of Econometric and Machine learning based models

- **Challenges include state dependency and stochastic nature of markets**
  - Time series
  - Overfitting/Underfitting
  - Stochastic Nature of Data

Artificial Intelligence



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Factor Analysis

- **Factor Analysis**
  - Identify factors that are driving the market and predict relative factor performance
  - Establish a portfolio of sectors or stocks that benefits from factor performance
  - Align risk management with forecasts of volatility
- **Identifying and Assessing factors driving performance**
  - Look at factors such as Value vs. Growth, Large Cap vs. Small Cap, Volatility

Best Performing Factors

Price/Book
Gross Margin
Price/Earnings
Cash/Assets
Market Cap(High-Low)

Worst Performing Factors

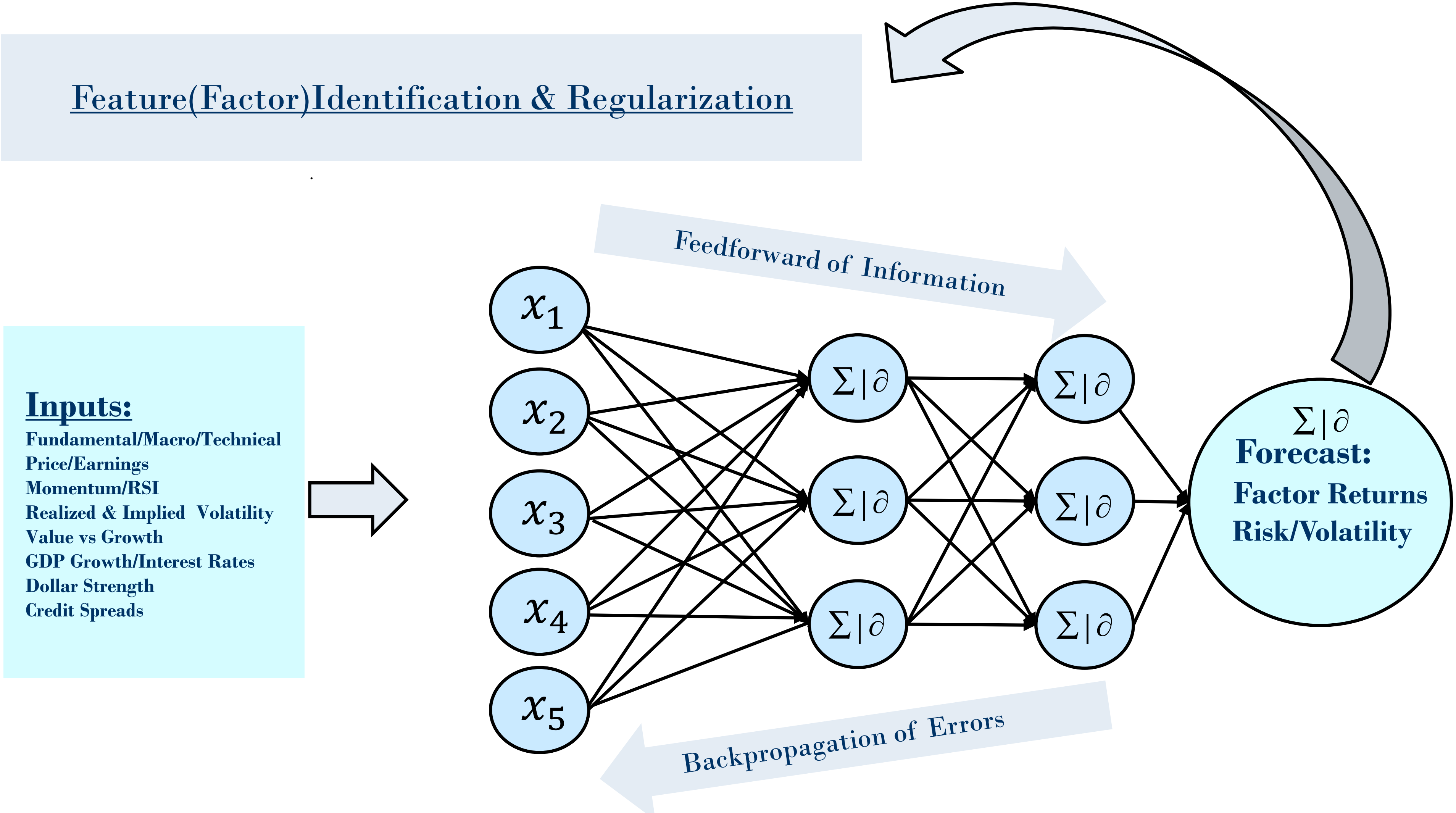
Volatility
EPS Growth
Dividend Payout
Debt/Equity
Capex/Sales

Period: 2018. Based on long/short monthly factor portfolios. This information is for illustrative purposes only.

Neural Networks

- **Static vs. Dynamic Neural Network**
  - Static vs Dynamic
  - Dynamic feedforward vs. feedback and recurrent connections
  - Focused Time Delay vs. Distributive Time Delay
- **Recurrent Neural Network**
  - Feedback output back through layers
  - LSTM captures the temporal nature of financial data

Static Neural Networks



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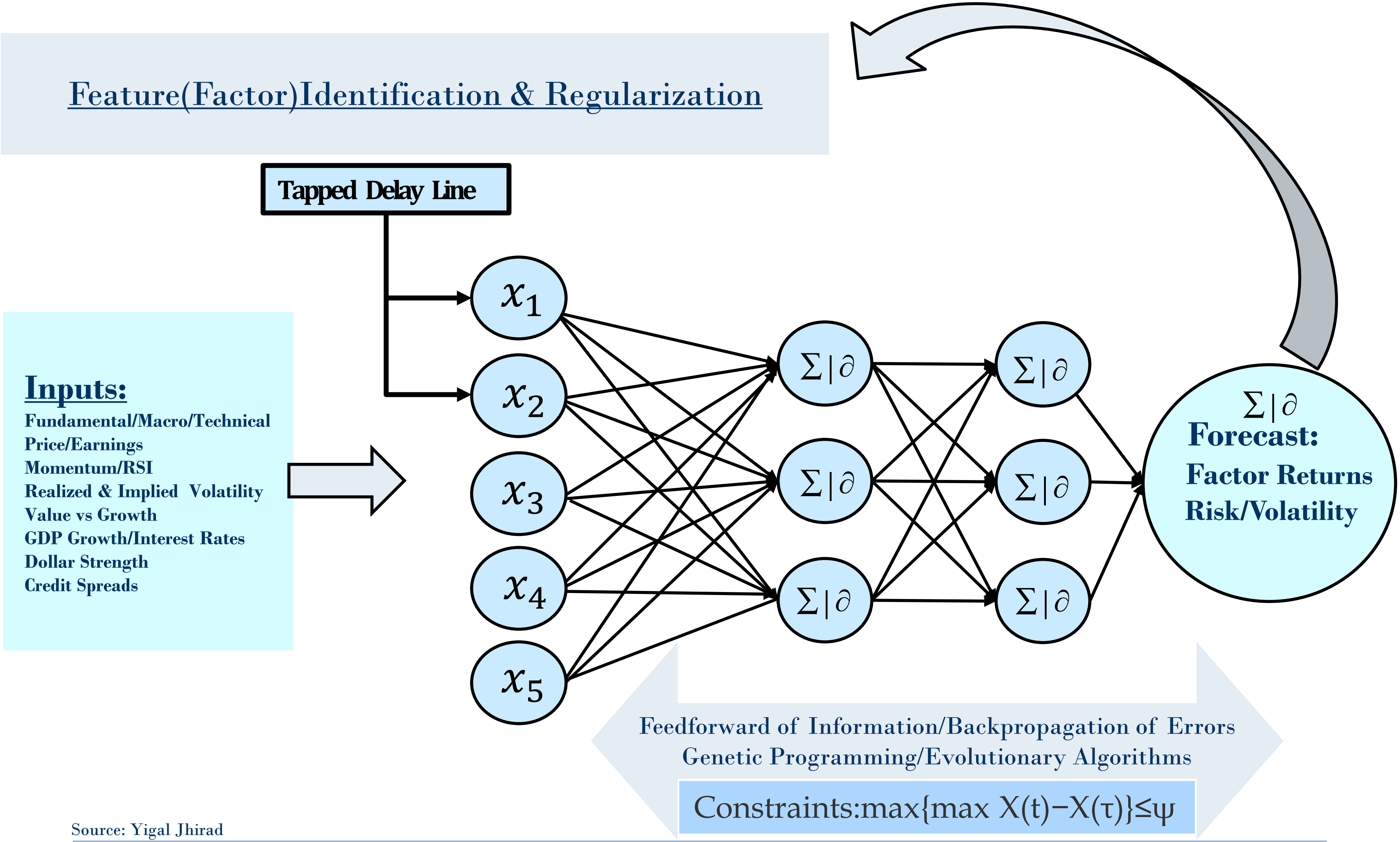
Dynamic Neural Networks



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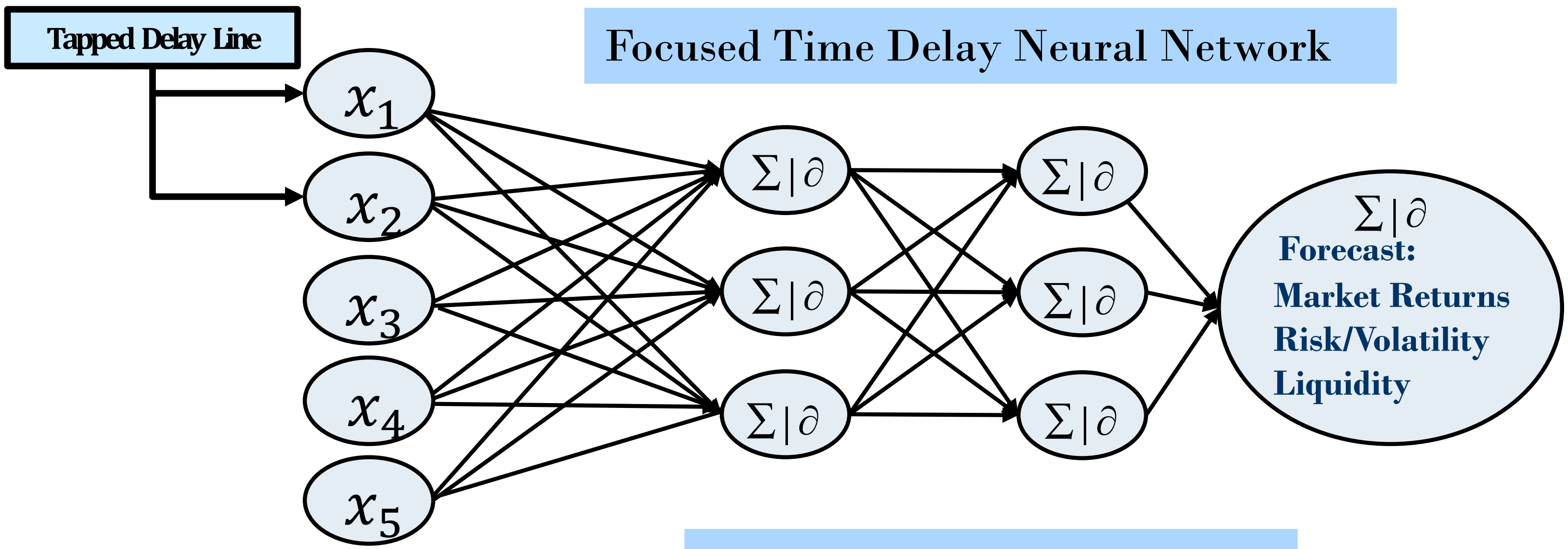
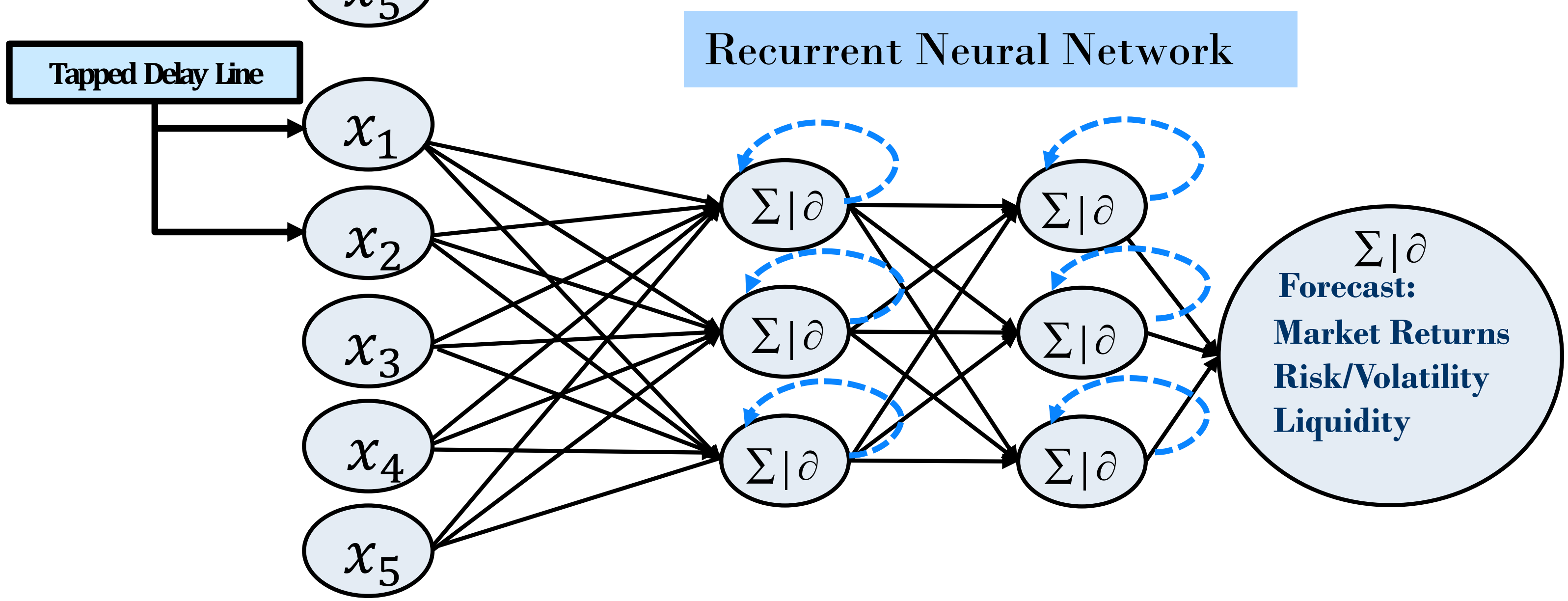
Supervised Learning: Neural Networks





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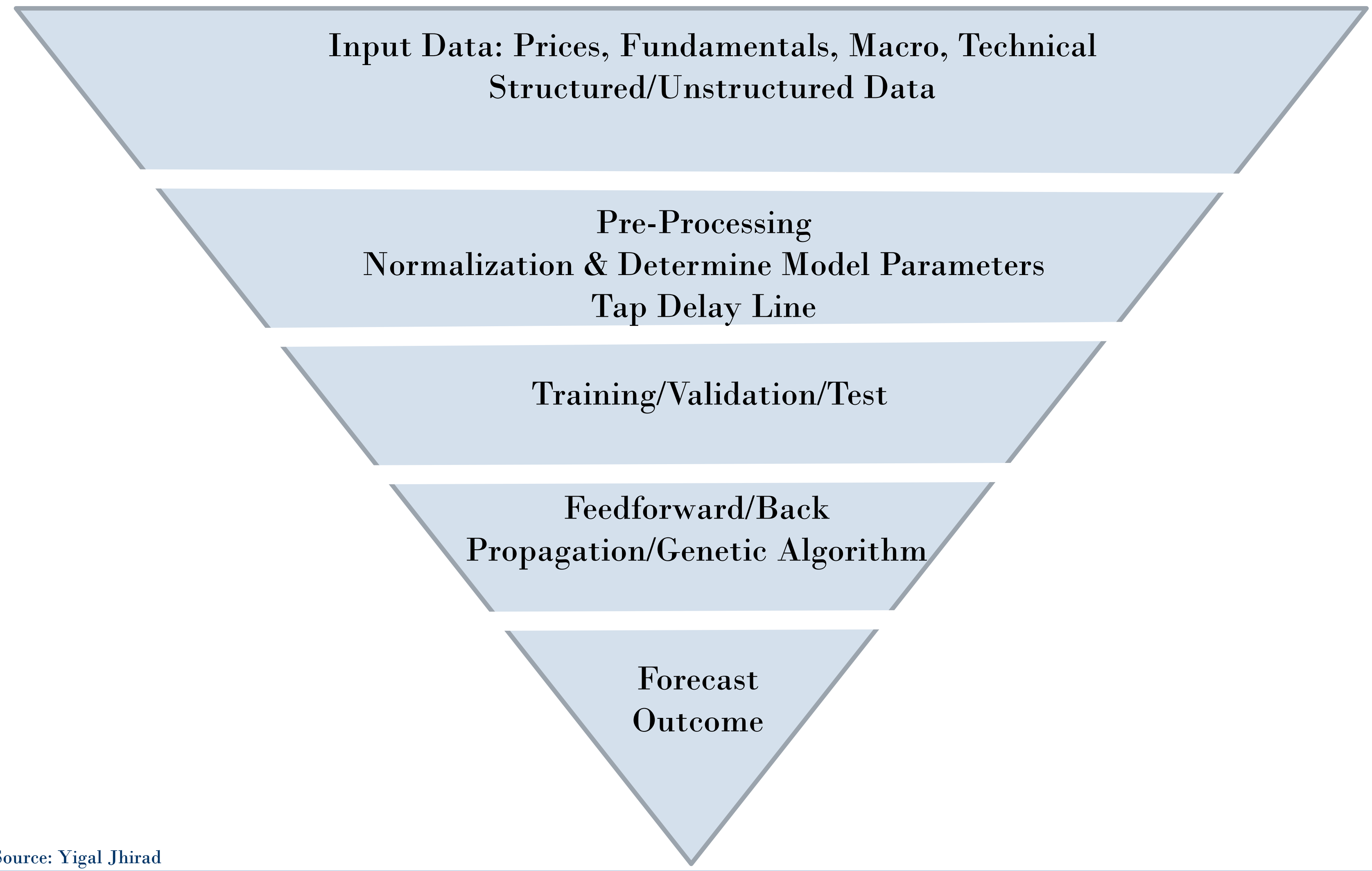
Neural Network Work Flow



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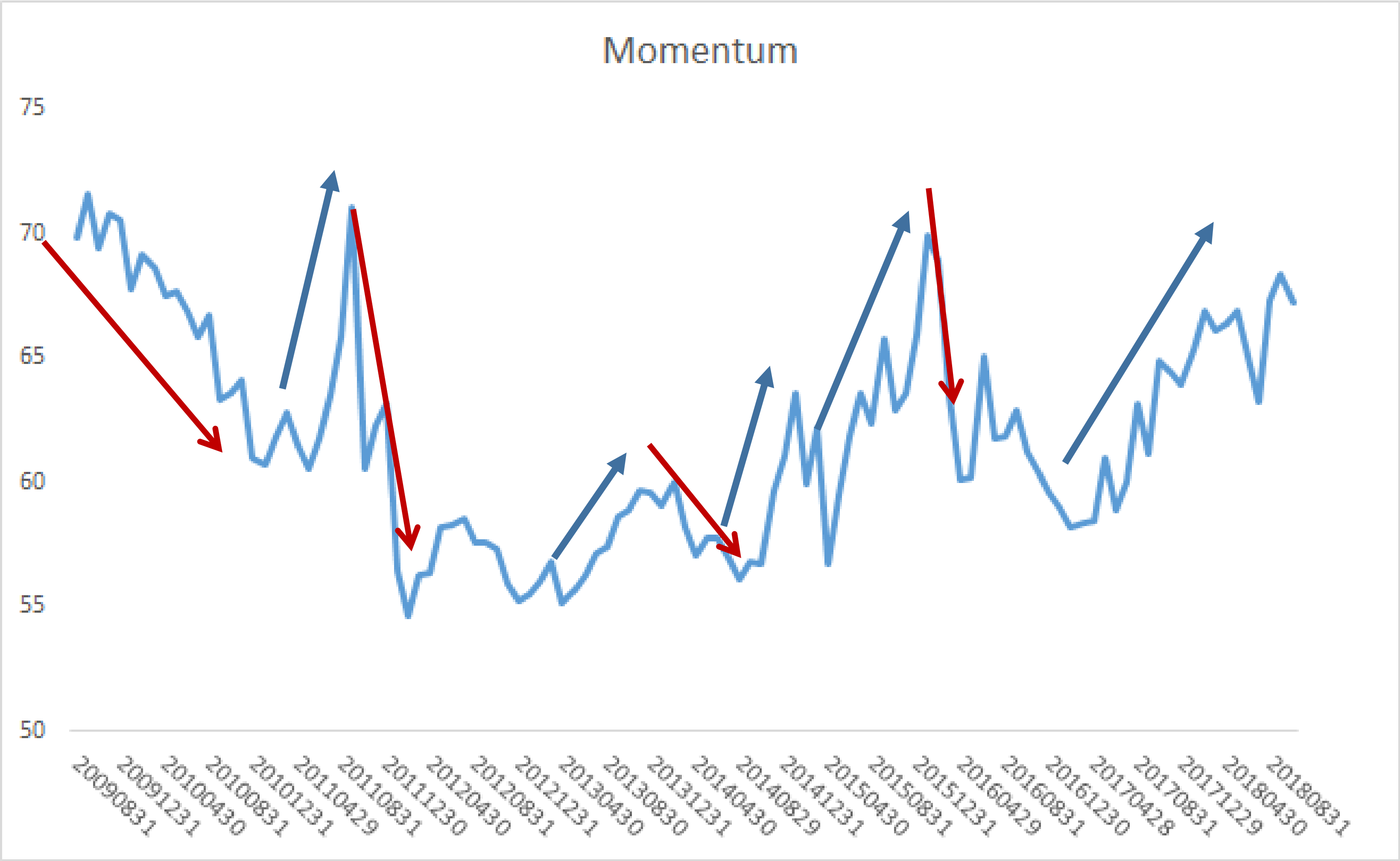
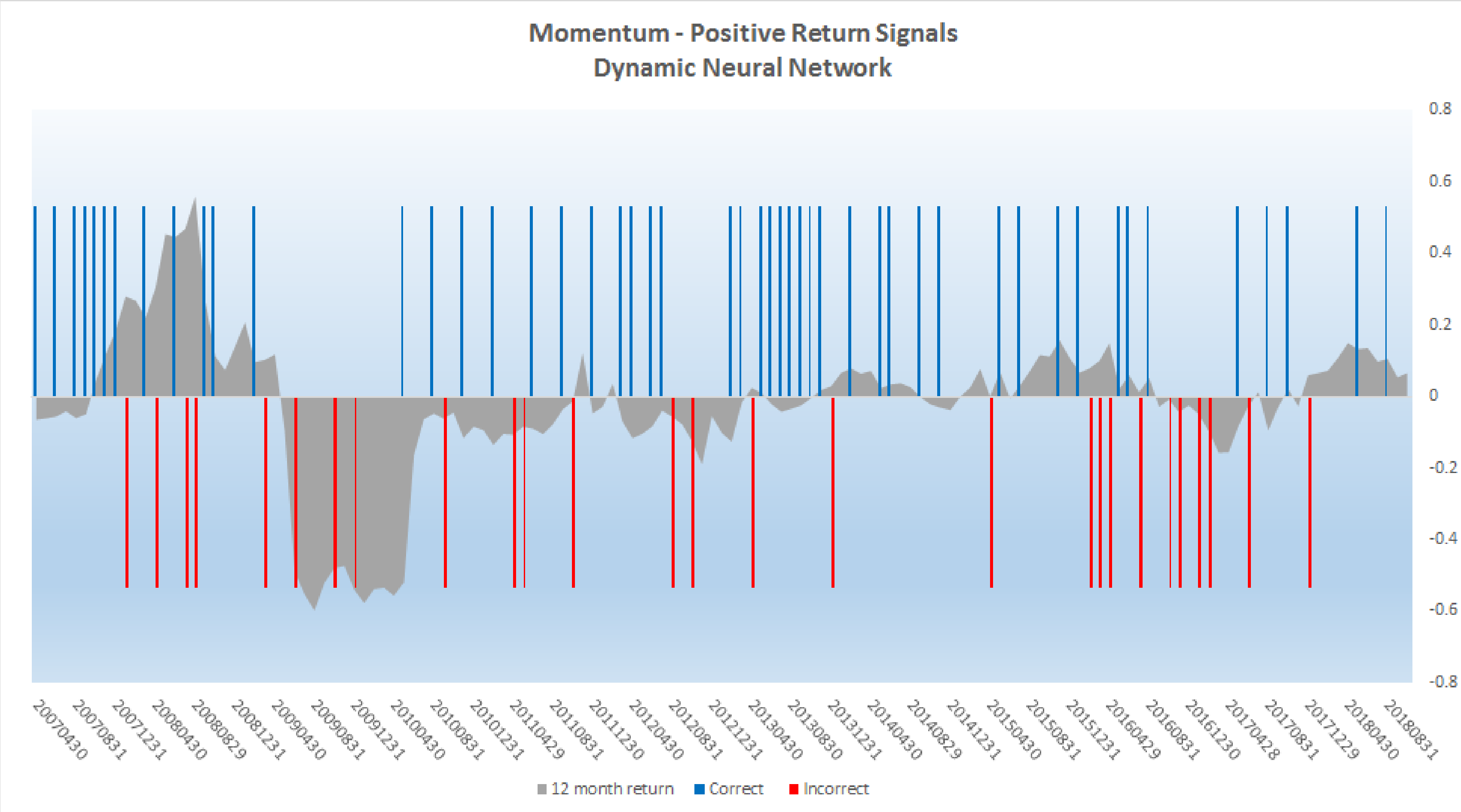
Predicting Factor Regimes



Period: 2009-2018. This information is for illustrative purposes only.

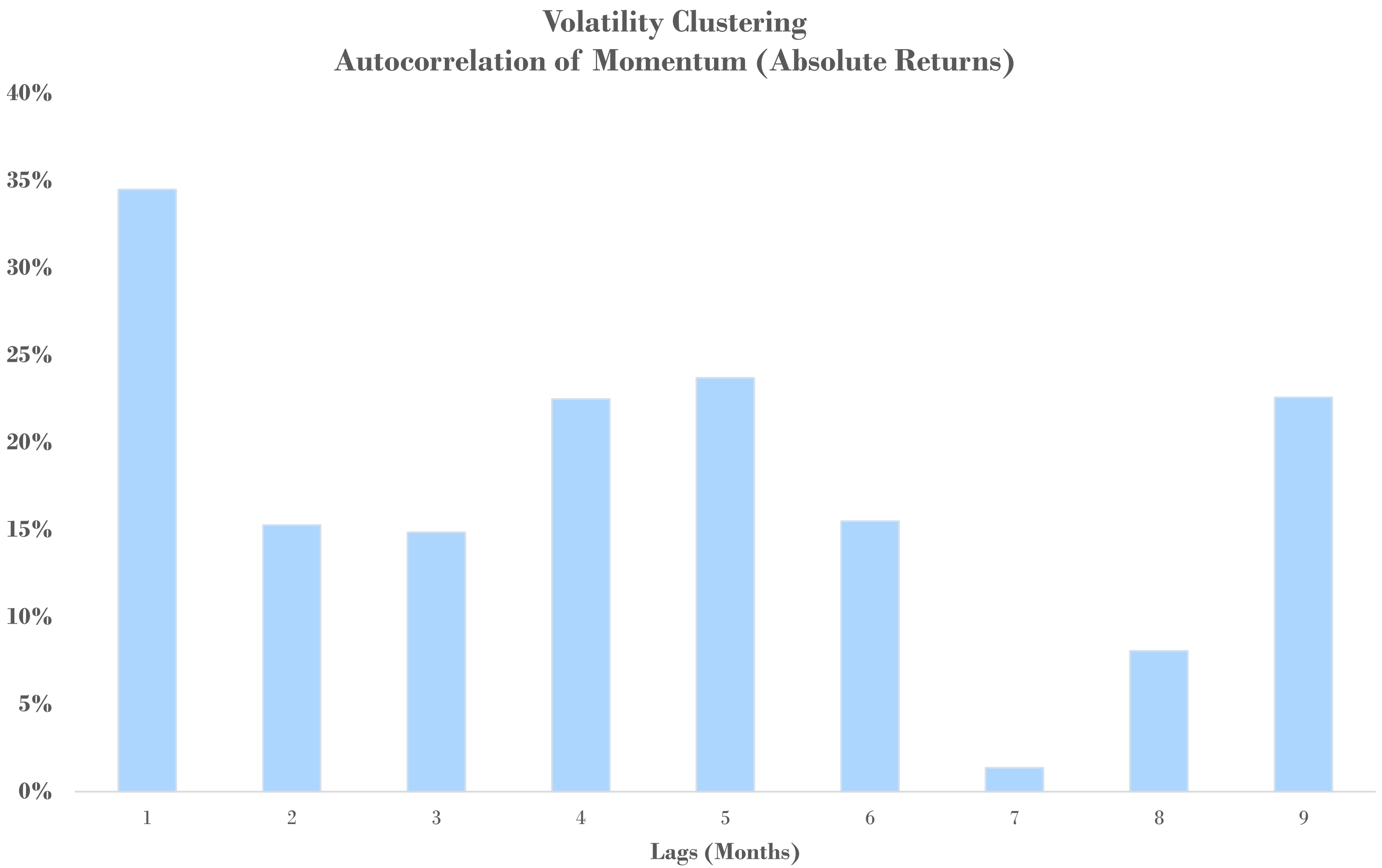
Predicting Factor Regimes



Prediction	Up	Down	Total	% Accuracy
Up	**49**	27	76	64%
Down	29	**34**	63	54%
Total	78	61	139	60%
% Realized	56%	44%		

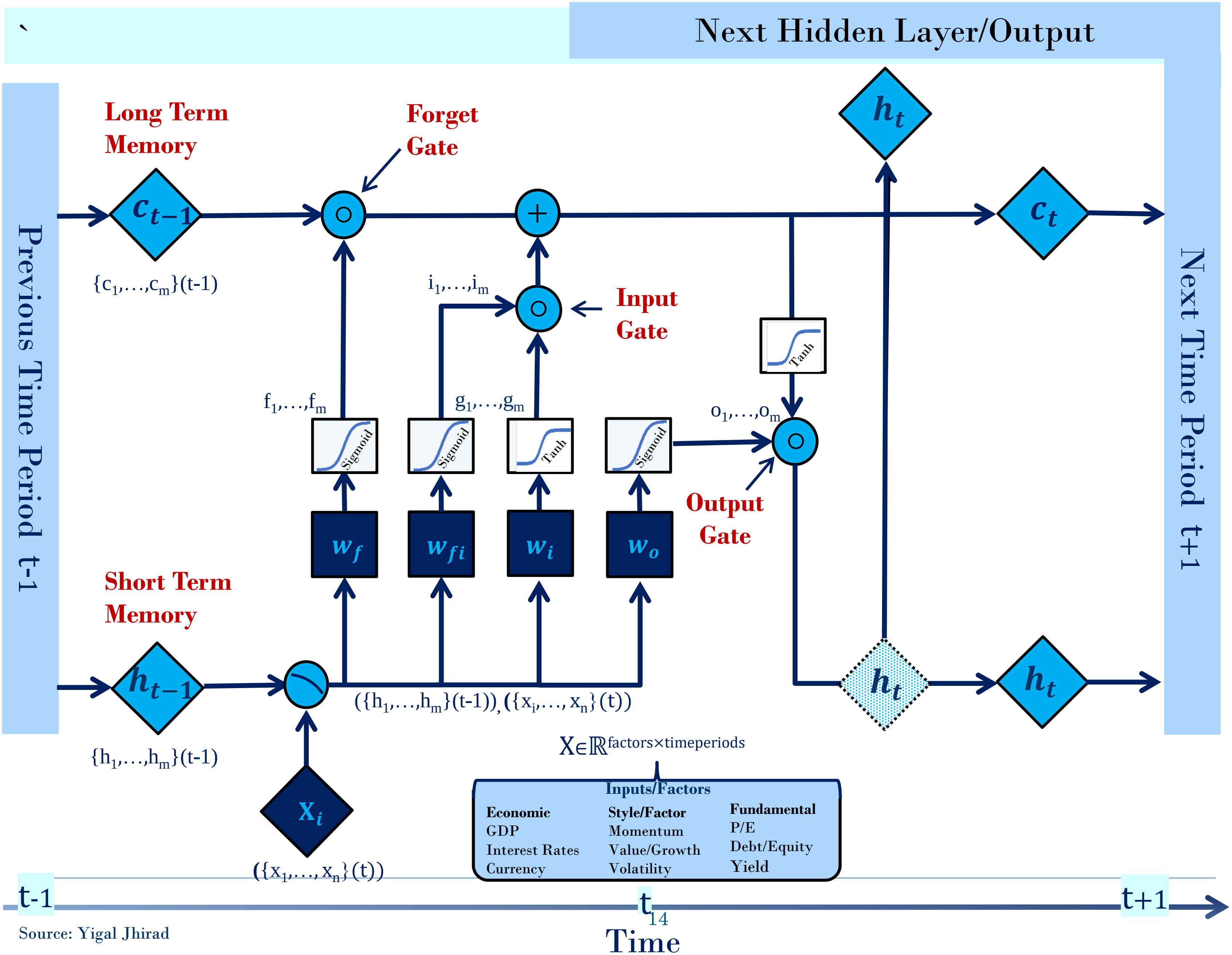
Period: 2007-2018. This information is for illustrative purposes only.

Predicting Factor Regimes



Period: 2004-2018. This information is for illustrative purposes only.

LSTM



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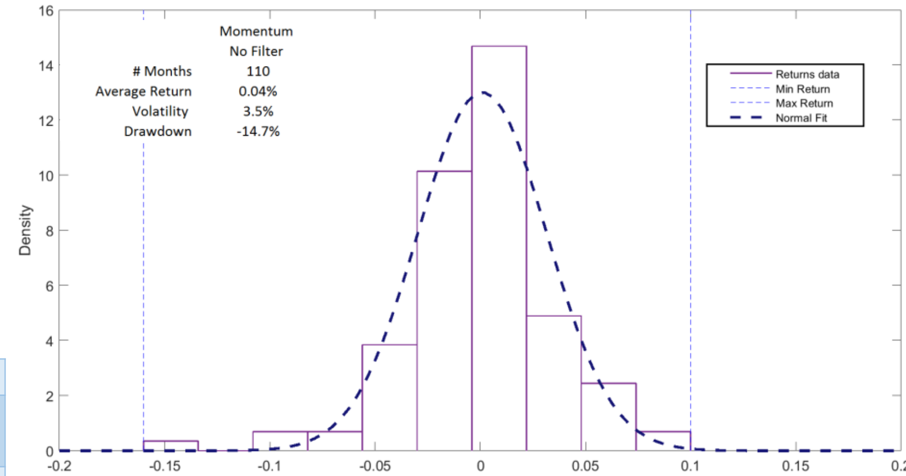
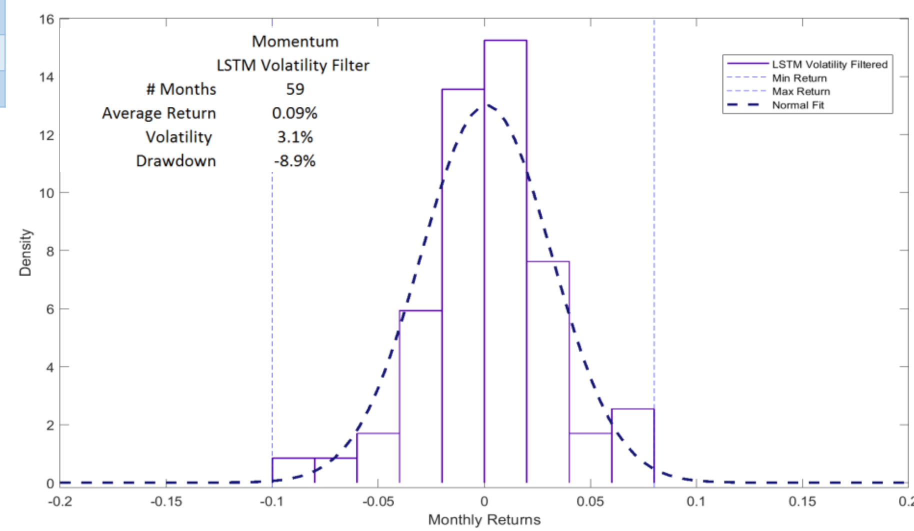
Volatility Signals using LSTM

- Build a Volatility Signal for Momentum to avoid periods of high dispersion
- Reduce overall volatility and minimize drawdowns

	Momentum	Momentum
	No Filter	LSTM Volatility Filter
# Months	110	59
Average Return	0.04%	0.09%
Volatility	3.5%	3.1%
Drawdown	-14.7%	-8.9%





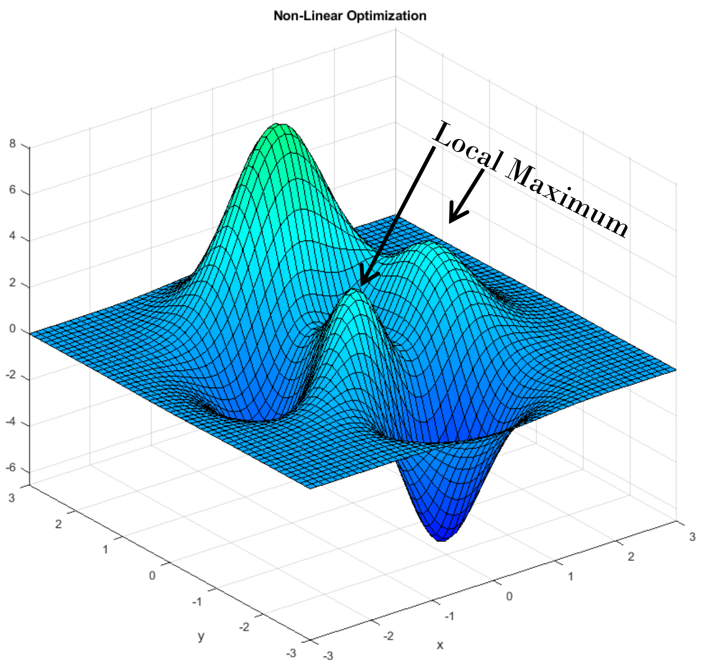
Period: 2004-2018. This information is for illustrative purposes only.

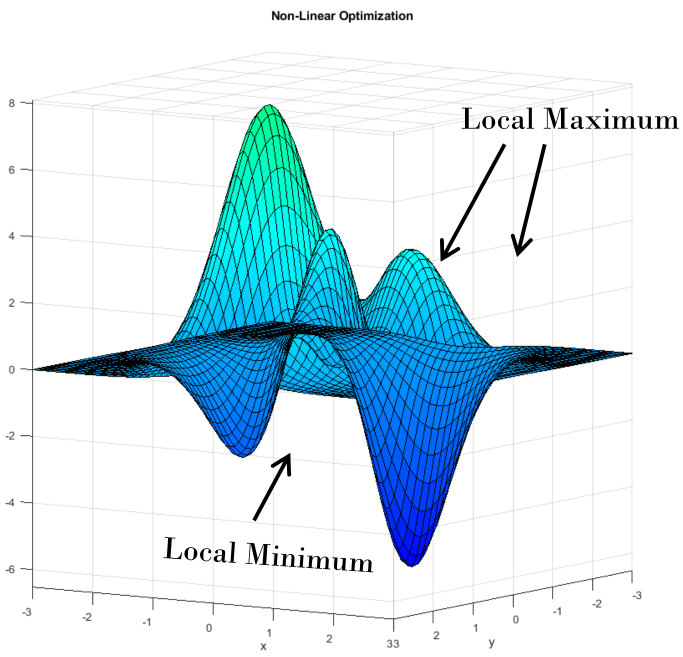
Neural Networks

- **Neural Networks**
  - Feed-Forward vs. Recurrent Neural Networks
  - LSTM and Time –Delay explicitly capture the temporal nature of financial data
  - Complement existing quantitative and qualitative signals
- **Advantages**
  - Captures non-linearity that are prevalent in financial data
  - Time Sequencing, Pattern Recognition
  - Modularity
  - Parallel Processing
- **Considerations**
  - Black Box
  - Overfitting/Underfitting
  - Optimization/Local Minima

Genetic Algorithms

- Genetic Algorithms complement traditional optimization techniques
- Gradient Descent may not be efficient. Local Minimums pose a challenge.
- Greater flexibility in imposing constraints
- Apply the computational power within CUDA to create a more robust evolutionary algorithm to drive multi-layer Neural Networks





Summary

- Focused Time-Delay and LSTM Neural Network may help identify volatility and factor regimes
- Enhance modeling by utilizing constrained optimizations and implementing genetic algorithms
- CUDA leverages GPU Hardware providing computational power to drive optimization algorithms and Deep Learning
- Application in Investment and Risk Management as part of an ensemble of econometric and machine learning based models

Author Biography

- **Yigal D. Jhirad,** Senior Vice President, is Director of Quantitative and Derivatives Strategies and a Portfolio Manager for Cohen & Steers' options and real assets strategies. Mr. Jhirad heads the firm's Investment Risk Committee. Prior to joining the firm in 2007, Mr. Jhirad was an executive director in the institutional equities division of Morgan Stanley, where he headed the company's portfolio and derivatives strategies effort. He was responsible for developing, implementing, and marketing quantitative and derivatives products to a broad array of institutional clients, including hedge funds, active and passive funds, pension funds and endowments. Mr. Jhirad graduated magna cum laude from the Wharton School with a Bachelor of Science in Economics. He is a Financial Risk Manager (FRM), as Certified by the Global Association of Risk Professionals.