Introduction to Microstructure and High Frequency Finance

Source: Hasbrouck, Empirical Market Microstructure & Notes
Tsay, Analysis of Financial Time Series

Financial Microstructure: Importance

1. Important in market design & operation, e.g. to compare different markets (NYSE vs NASDAQ)

2. To study price discovery, liquidity, volatility, etc.

3. To understand costs of trading

4. Important in learning the consequences of institutional arrangements on observed processes, e.g.

   - Nonsynchronous trading
   - Bid-ask bounce
   - Impact of changes in tick size, after-hour trading, etc.
   - Impact of daily price limits (many foreign markets)

High frequency financial data

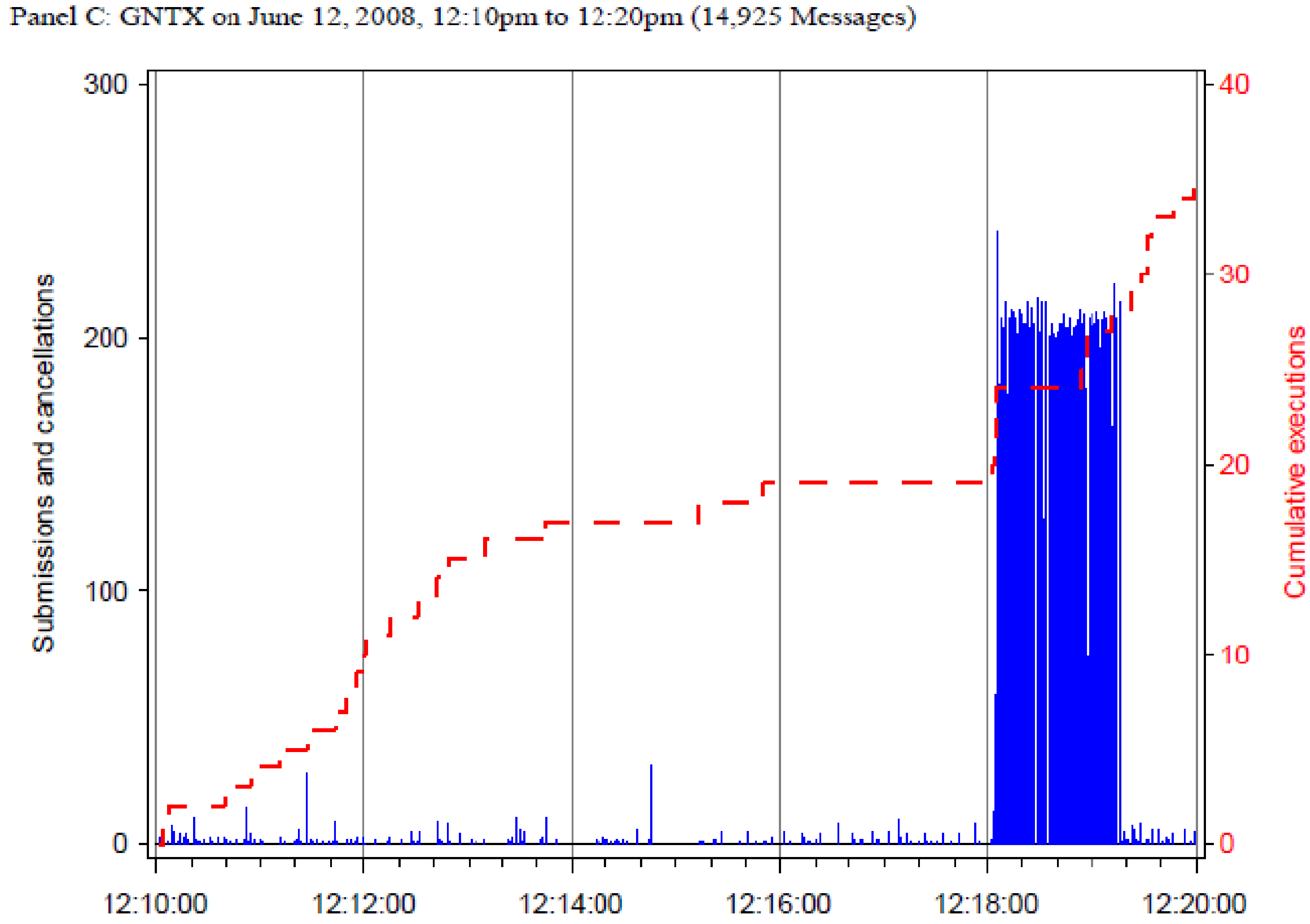
Observations taken with time intervals 24 hours or less

Some example:

1. Transaction (or tick-by-tick) data
2. 5-minute returns in FX
3. 1-minute returns on index futures and cash market

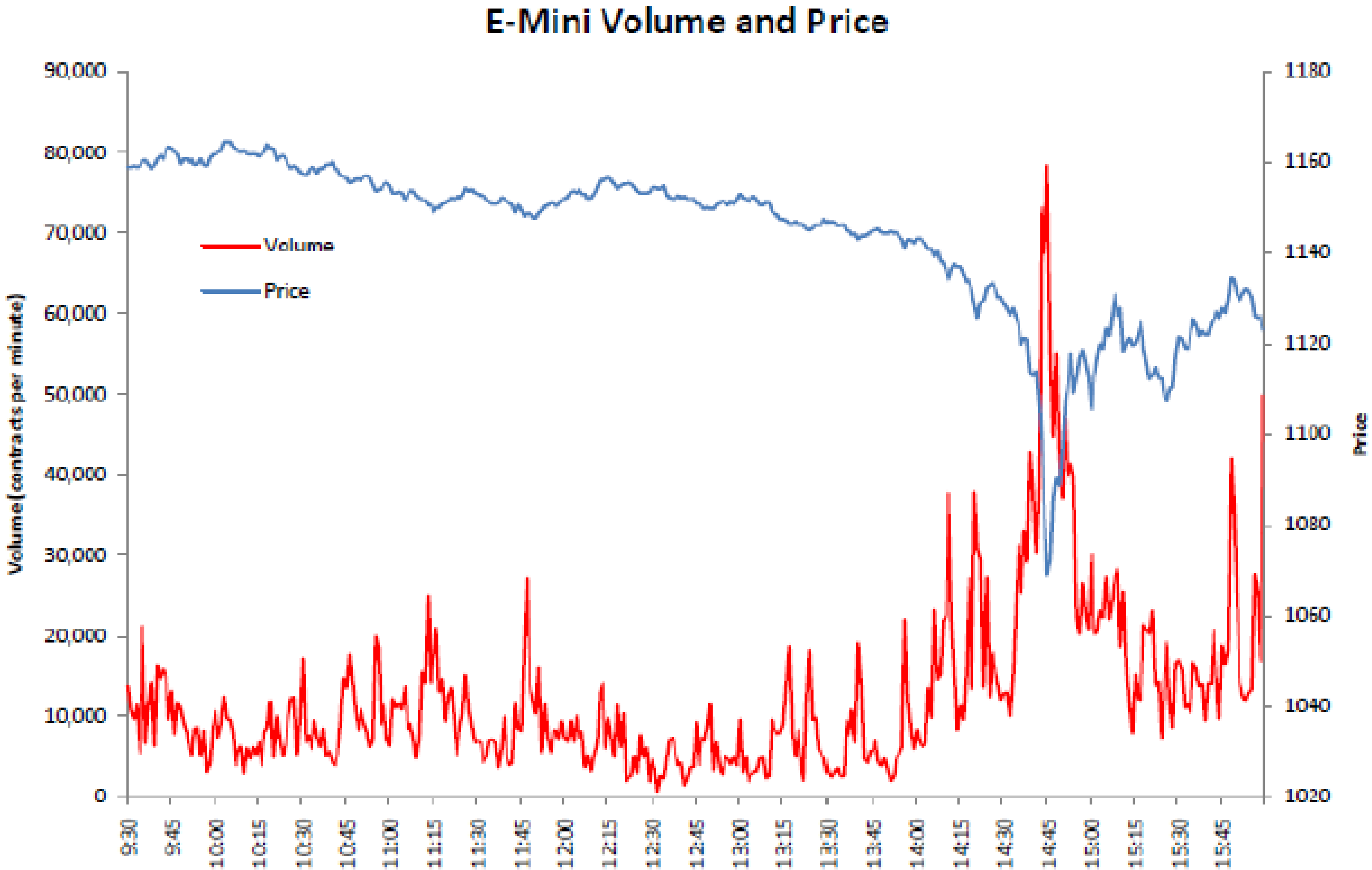
Some Basic Features of the Data:

1. Irregular time intervals
2. Leptokurtic or Heavy tails
3. Discrete values, e.g. price in multiples of tick size
4. Large sample size
5. Multi-dimensional variables, e.g. price, volume, quotes, etc.
6. Diurnal Pattern



High frequency trading can be intense and abrupt.

Flash crash, May 6, 2010



US stocks indexes: sharp decline (5-6%) over a few minutes, followed by a quick rebound.

Flash Crash CFTC Report

In the index:
At 2:32 p.m., … a large fundamental trader (a mutual fund complex) initiated a sell program to sell a total of 75,000 E-Mini contracts (valued at approximately $4.1 billion) as a hedge to an existing equity position.
…
This large fundamental trader chose to execute this sell program via an automated execution algorithm (“Sell Algorithm”) that was programmed to feed orders into the June 2010 E-Mini market to target an execution rate set to 9% of the trading volume calculated over the previous minute, but without regard to price or time (CFTC report).

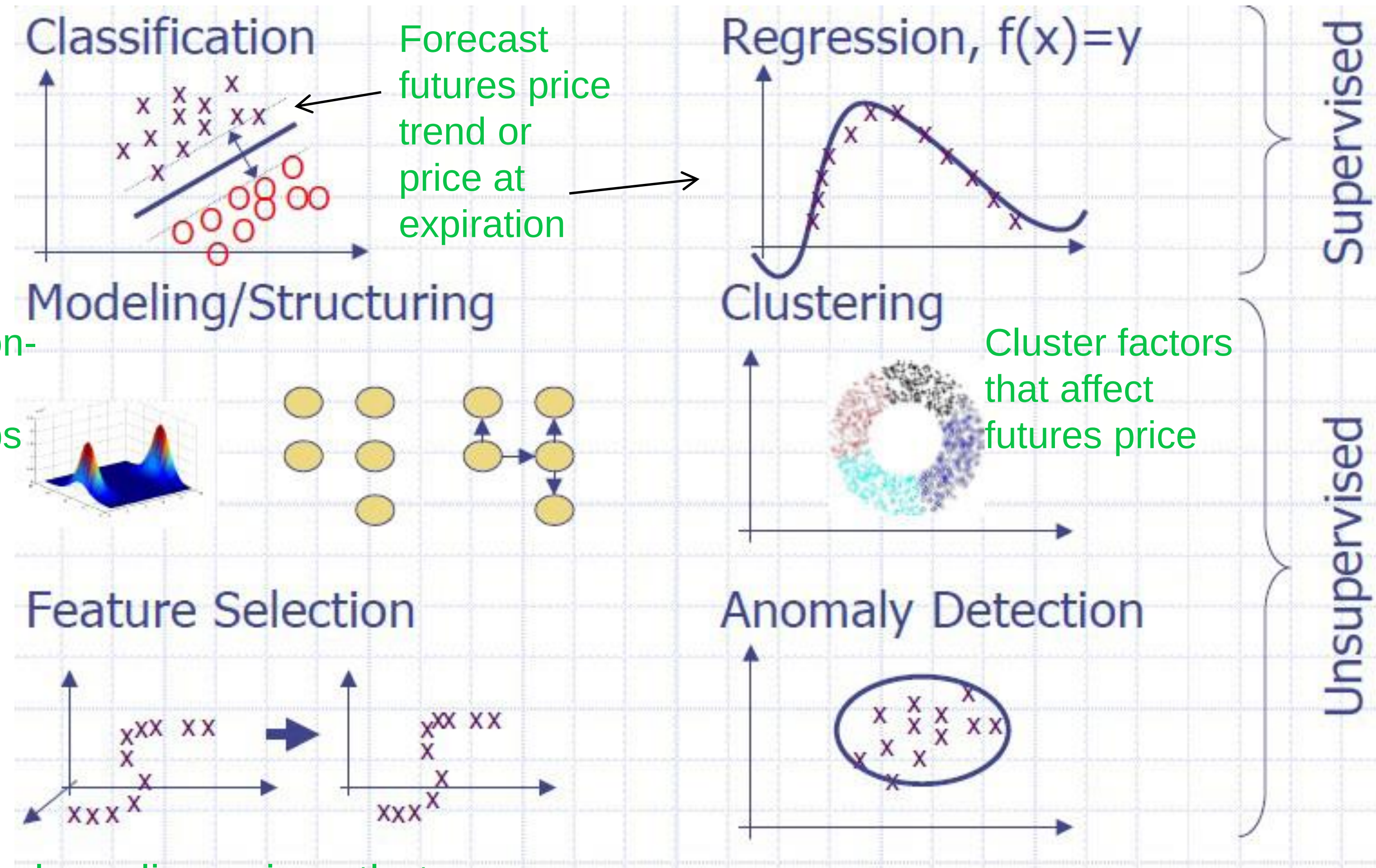
Trading requires finding patterns in massive..

amounts of information in (semi) automated way → Machine Learning

Objective of this presentation:

- Overview of cutting-edge developments in machine learning and how financial markets are applying these principles
- Deeper exploration of a machine learning method that may lead to uncovering profit opportunities
- How technique work in practice

Machine learning: statistical data-driven computational models



Forecast futures price trend or price at expiration

Uncover non-linear relationships among variables

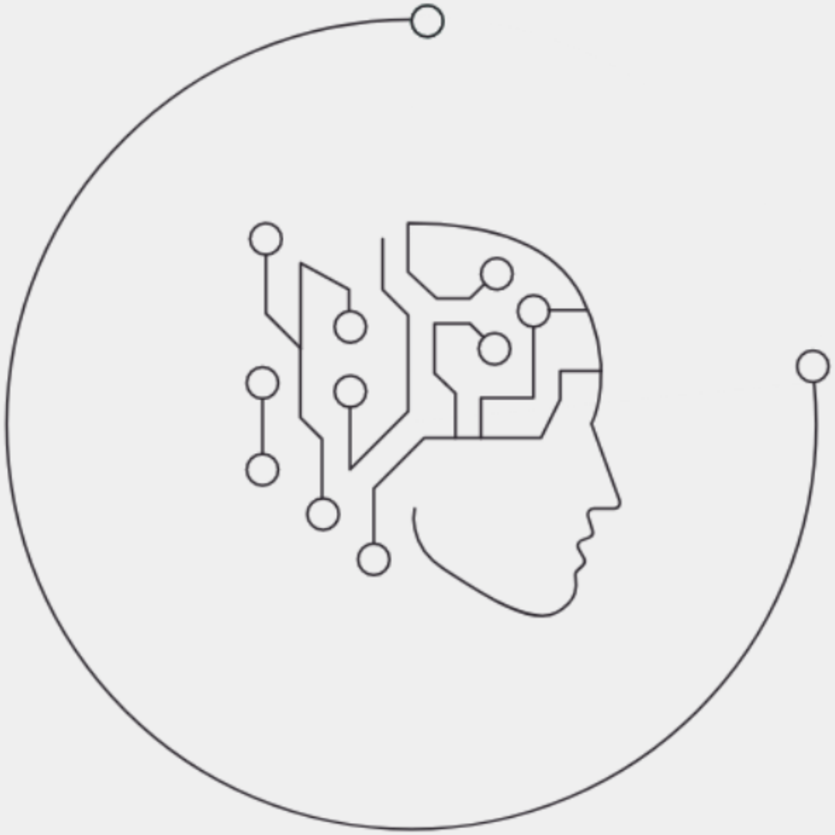
Cluster factors that affect futures price

Reduce dimensions that explain futures price

Find out outliers that may affect futures price forecast

Machine learning (ML) applications in finance

Artificial Intelligence in Financial Services



77%

of respondents anticipate AI will "possess high or very high overall importance to their businesses within two years."

Source: "Transforming Paradigms: A Global AI in Financial Services Survey," Cambridge Centre for Alternative Finance and the World Economic Forum, January 2020.

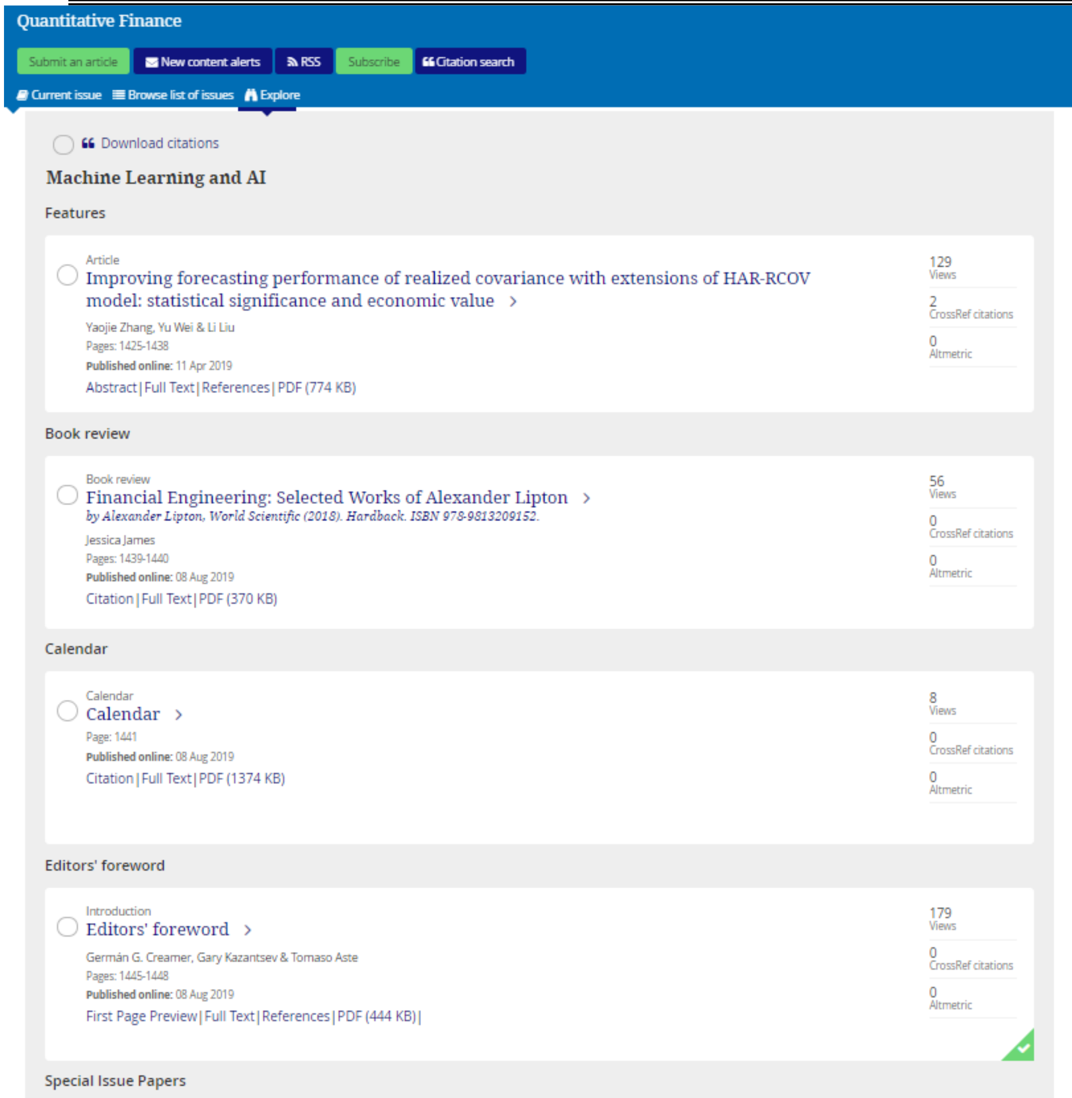
Machine learning (ML) applications in finance

- Microstructure and algorithmic trading:
  - Replication of technical analysis and time series patterns
  - Generation of new trading rules & optimal combination of existent trading rules
- Portfolio optimization:
  - Use ML to propose financial scenarios (investors' view) in Black Litterman model
- Equity valuation and fundamental analysis:
  - Decision trees or Bayes Nets to define main drivers of corporate profitability and equity value
- Financial forecasting: using financial time series with unstructured data (images, text [news, tweets…] to forecast financial trends
  - Anticipate major events at the macro or at the customer level
- Risk management: Credit rating and customer segmentation
- Consumer analytics:
  - Managing customer data: extract behavioral information from customers' decisions and transactions
    - Social networks & access to new investors through current customers
- Personalization and customization: get to know the customer to offer the best product/advice.
- Fraud detection

Quantitative Finance Journal Special issue: Machine learning and AI

Vol. 19, 2019

https://www.tandfonline.com/toc/rquf20/19/9?nav=tocList



- Forecasting:
  - Universal Model
  - Prediction Markets
  - Liquidity
  - Market Cycle
  - Stock Price Forecast
- Microstructure
- Causality
- Option Pricing
- Testing Investment Strategies

Energy Economics Journal: Machine learning in energy economics and finance

ELSEVIER

Energy Economics
Volume 81, June 2019, Pages 709-727

Machine learning in energy economics and finance: A review

Hamed Ghoddusi [a], Germán G. Creamer [a], Nima Rafizadeh [b]

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https://doi.org/10.1016/j.eneco.2019.05.006

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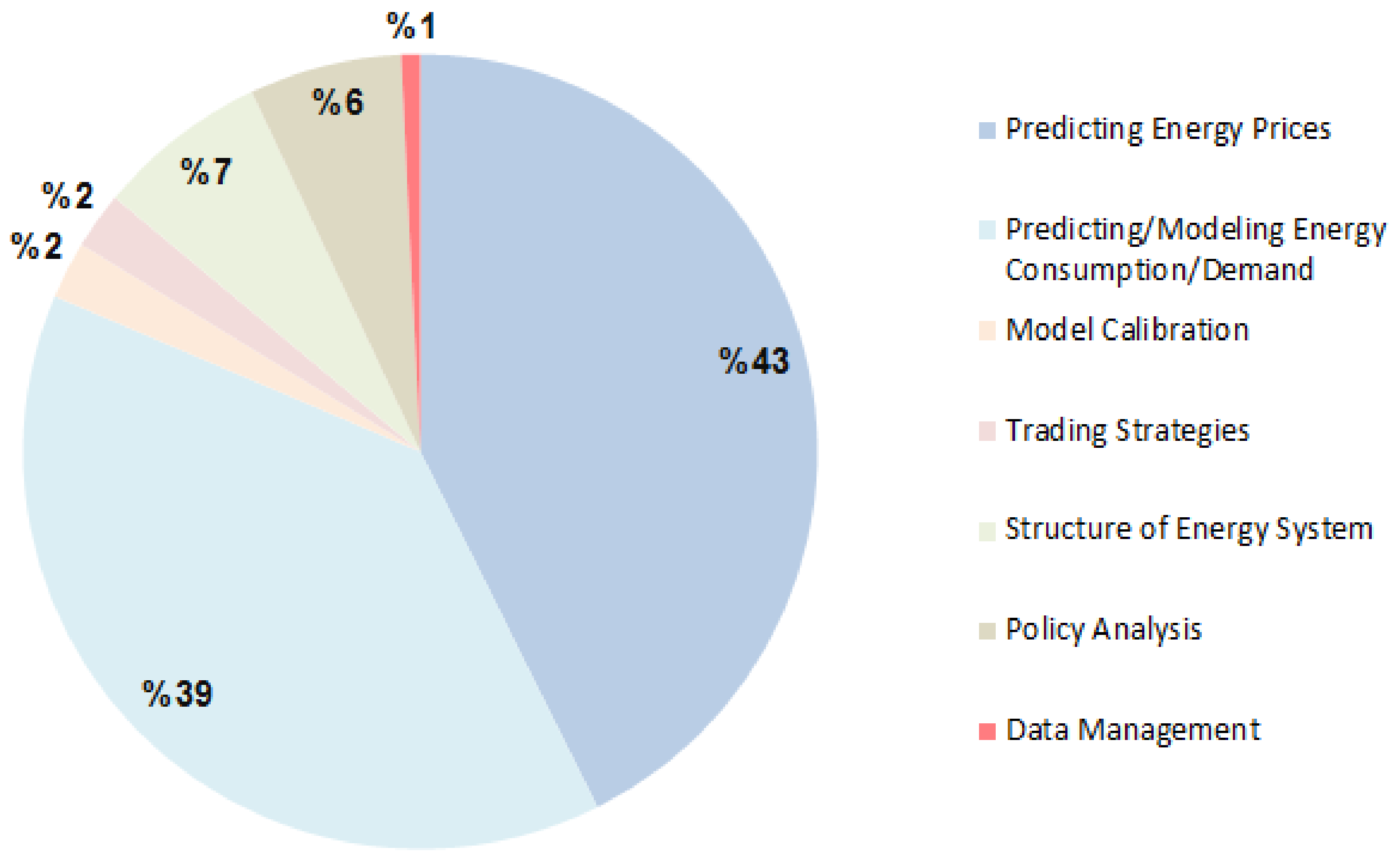
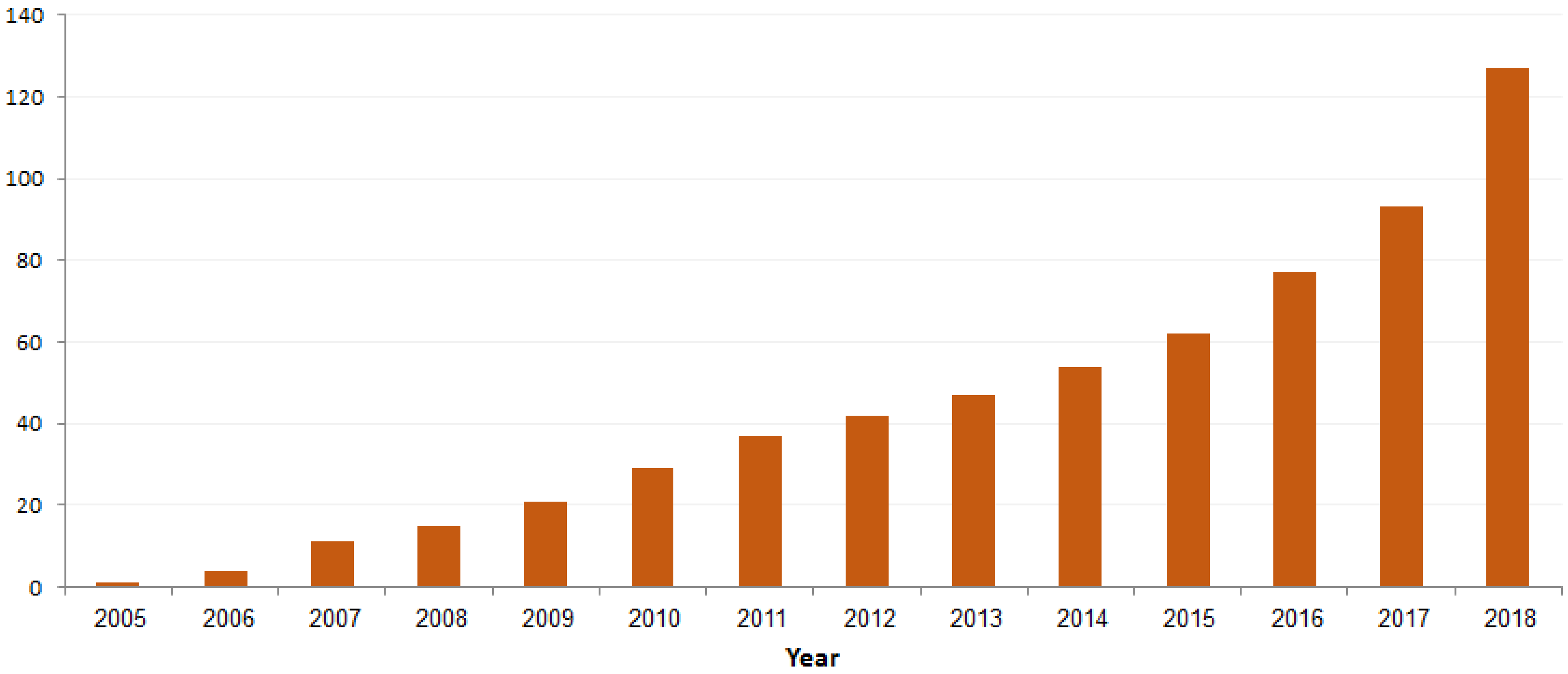
Highlights

- First comprehensive review of machine learning in energy economics
- Identified more than than 120 papers published in this area
- Support-Vector-Machine and Artificial Neural Networks found to be the most popular methods
- Crude oil and electricity price predictions are the two most frequent domain applications.
- Opportunities to apply ML techniques to energy-related volatility prediction, social network analysis, and text processing

Machine learning in energy economics and finance: Relative Frequency of Application Domains



Machine learning in energy economics and finance: Cumulative number of publications: 2005-2018



There is a growing area of research applying machine learning methods to formulate trading strategies using technical indicators

- Part of the problem of the studies during the 60s is the ad hoc specifications of the trading rules → data snooping
- Ex post specification of rules may lead to biased studies.

- What about if technical analysis indicators are used as indicators and machine learning or optimization methods find the appropriate specification of the rules and parameters to take the investment decision or forecast future prices?

Technical analysis detects and interprets patterns…

…in past futures prices based on charts to make future investment decisions

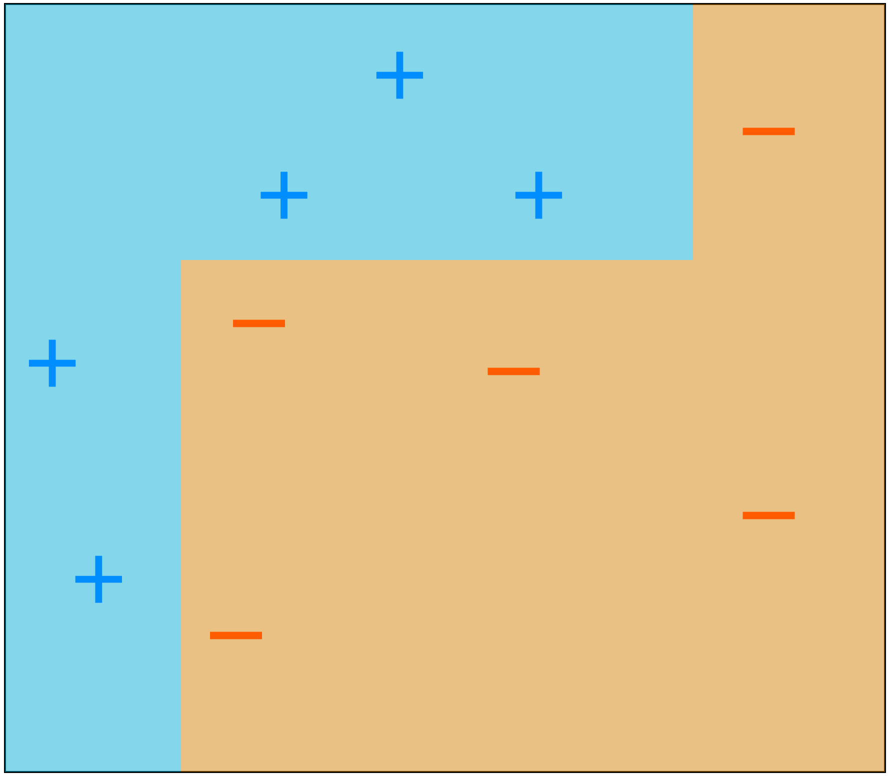
- It shares with machine learning the interest on pattern recognition
- Formalizes traders' thinking:
  - "buy when it breaks through a high"
  - "sell when it is declining", etc.
- Type of indicators:
  - Price
  - Momentum and oscillation indicators
  - Volatility indicators
  - Volume indicators…

Boosting: a method for improving classifier accuracy

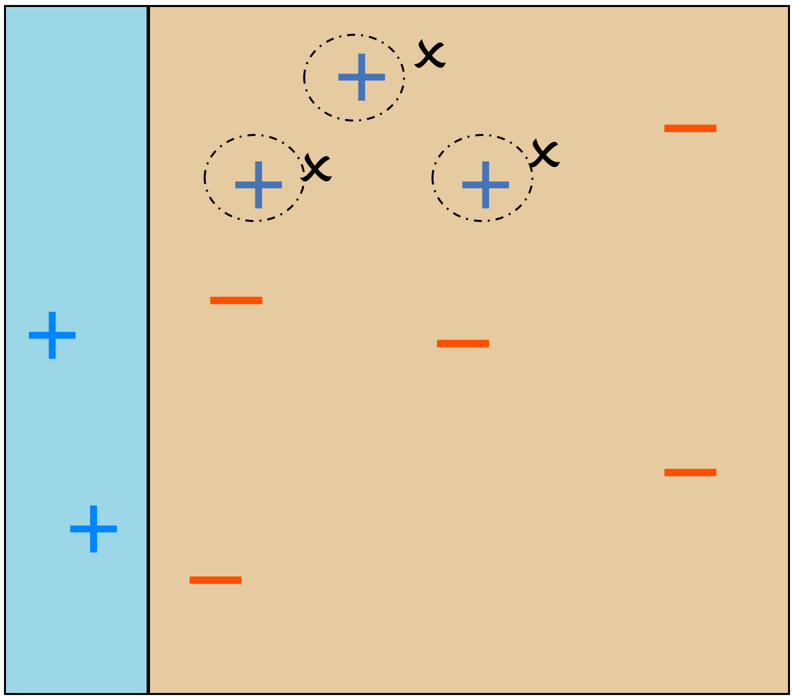
Freund, Schapire 1997

- Basic idea:
  - Perform iterative search to locate the regions/ examples that are more difficult to predict.
  - Through each iteration reward accurate predictions on those regions.
  - Combines the rules from each iteration.
- Only requires that the underlying learning algorithm be better than guessing.

Example of a Good Classifier



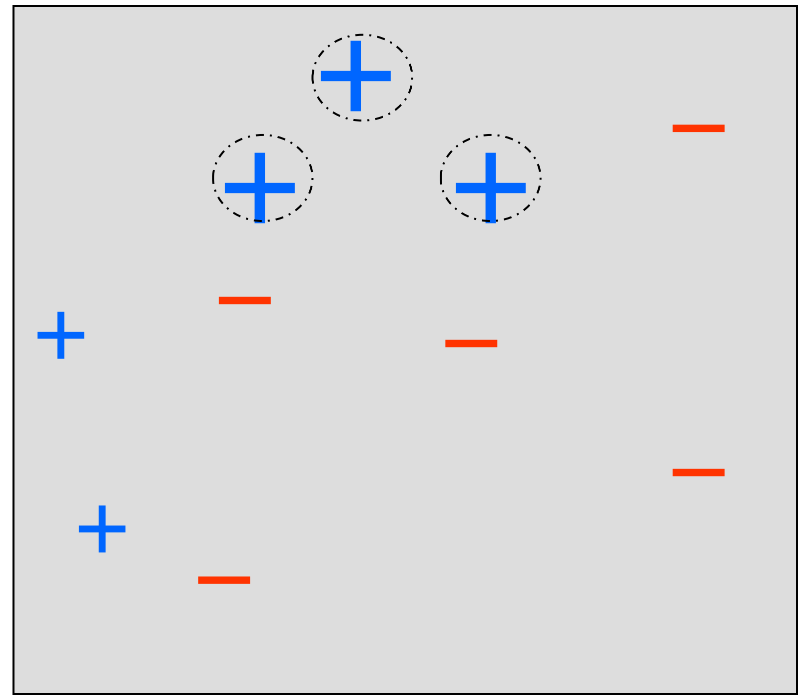
Round 1 of 3



h_1

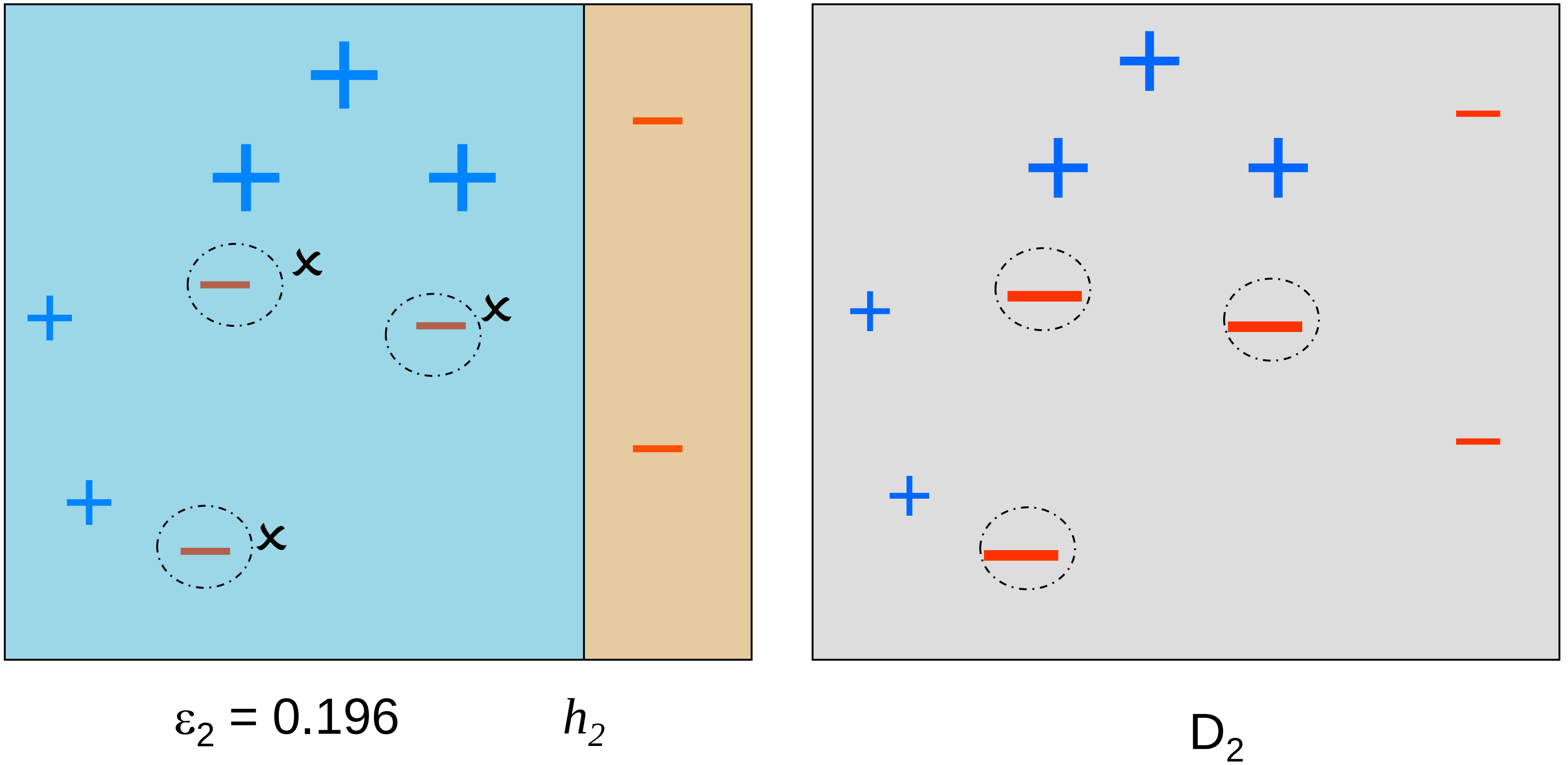
$\varepsilon_1 = 0.300$

$\alpha_1 = 0.424$



D_2

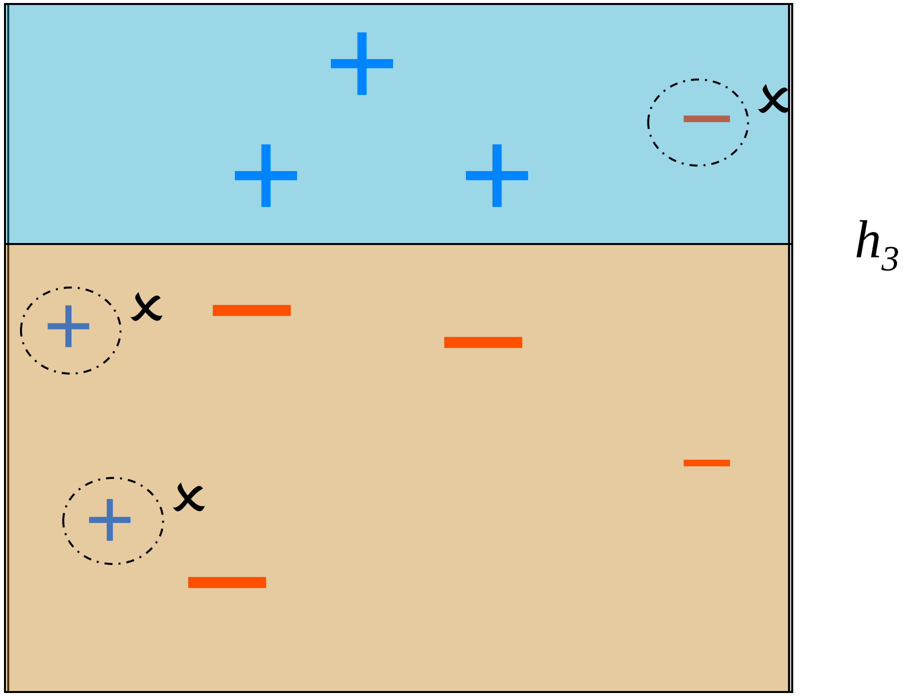
Round 2 of 3



$\varepsilon_2 = 0.196$

$\alpha_2 = 0.704$

Round 3 of 3

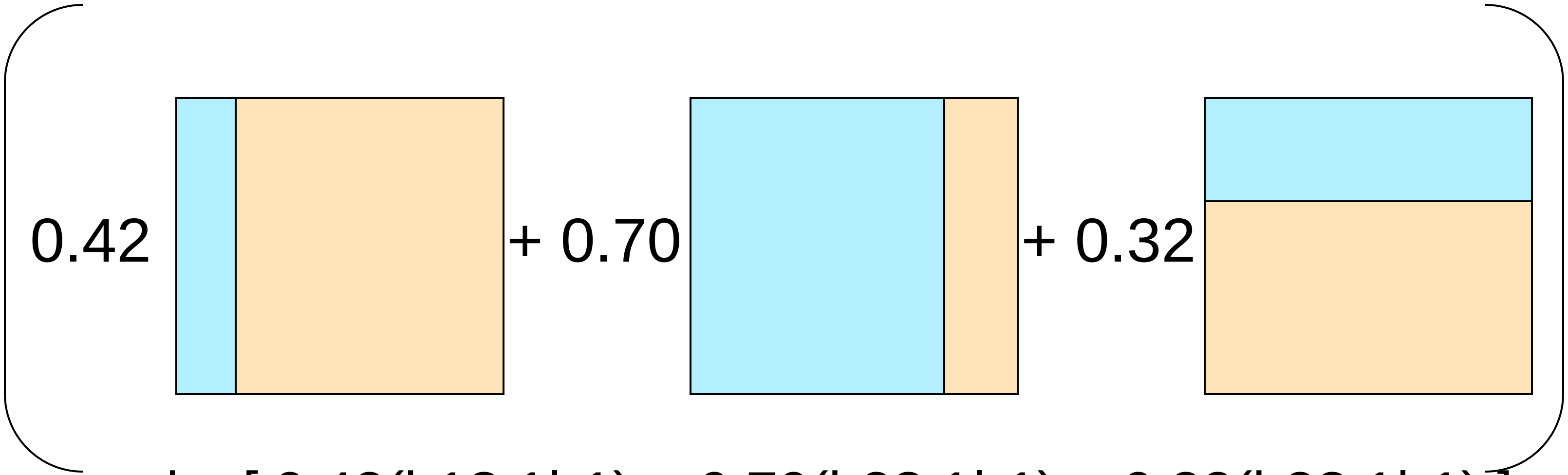


STOP

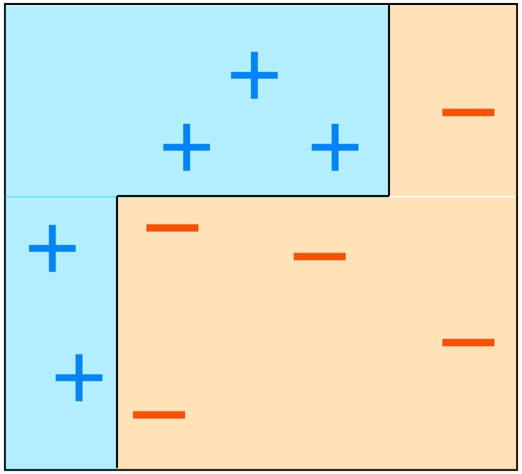
$\varepsilon_3 = 0.344$

$\alpha_2=0.323$

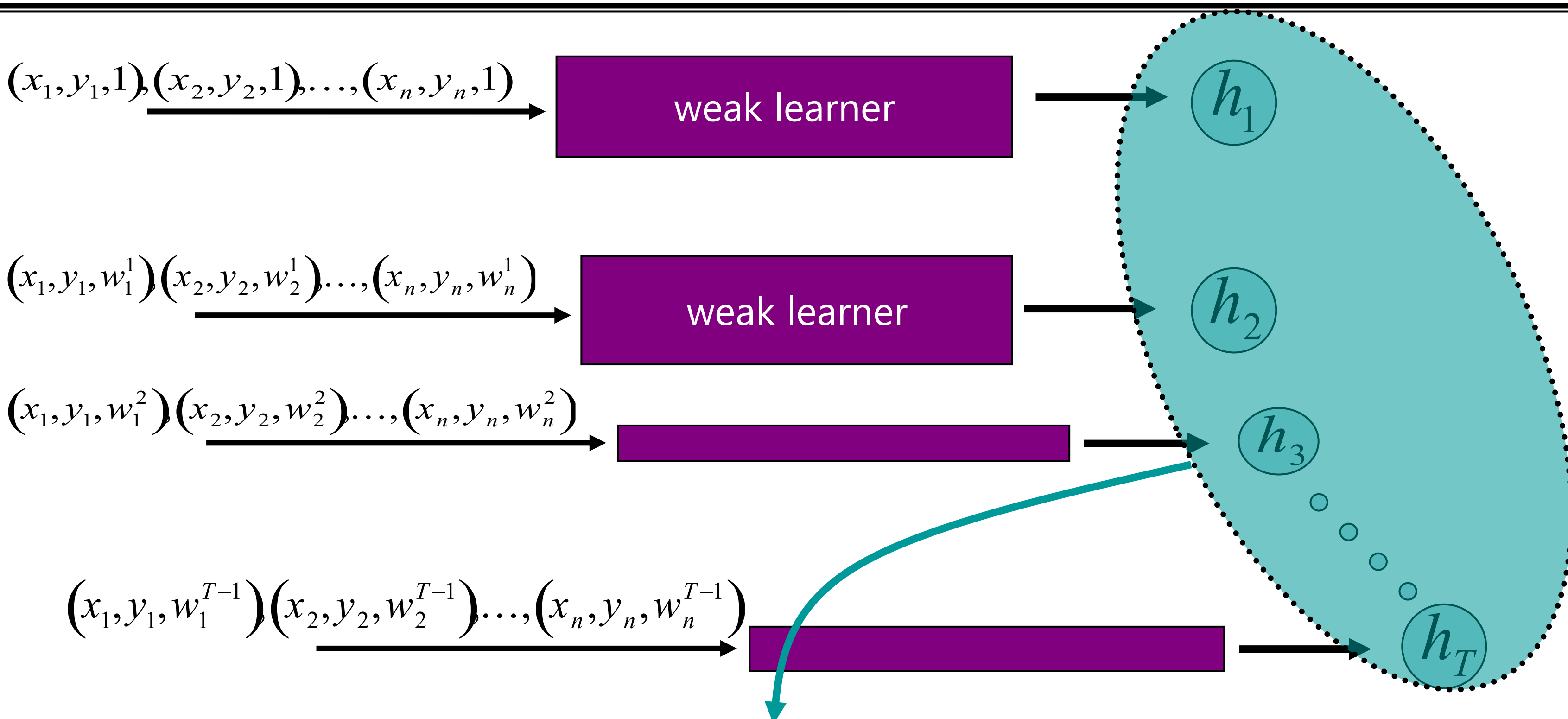
Final Hypothesis



H_{final} = sign[0.42(h1? 1|-1) + 0.70(h2? 1|-1) + 0.32(h3? 1|-1)]



The boosting process: General discriminative learning algorithm (Freund & Schapire, 1997)

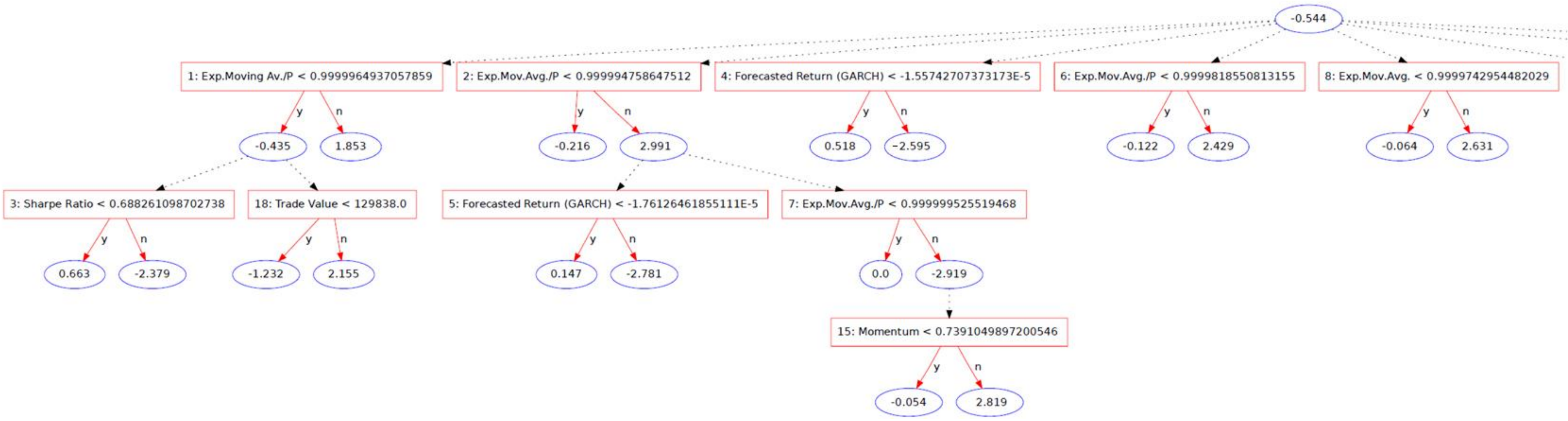


$$F_T(x) = \alpha_1 h_1(x) + \alpha_2 h_2(x) + \cdots + \alpha_T h_T(x)$$

Final rule: $f_T(x) = \operatorname{sign}(F_T(x))$

Logitboost is a modification of Adaboost and is an algorithm for step-wise logistic regression (Friedman et al. (2000)).

Rules of boosting: alternating decision tree (ADT) for investment decisions



ADT for EURO STOXX 50 ® Index Futures (FESX), 03-04-2009

Feature Selection and Model calibration

How to select an optimal combination of parameters that optimize technical indicators?

Why use the same number (2) of standard deviations to calculate Bollinger bands?

Calibration methods:

- Brute force: try large number of alternatives and select the best.
  - Problem: computationally intense and high frequency data may change significantly in different periods, then it may require continuous calibration
- Genetic algorithms (Núñez, 2007; Bodas-Sagi *et al* 2009): multi-objective optimization using genetic algorithm where parameters take different values within a range until optimal point is reached (similar to simulated annealing)
- Our approach (Creamer, 2011): input to the model are same technical indicators calculated with different parameters. Based on a ML method, such as boosting, that has a strong feature selection capability, build a model only with the optimal combination of parameters. Every time that a model is built, parameters are also optimized

Source: G. Creamer (2012). “Model Calibration and Automated Trading Agent for Euro Futures.” Quantitative Finance 12 (4): 531-545.

Example Bollinger Bands: 20d mov avg +/- 2SD

Feature Selection and Model calibration

Example of our method with Bollinger Bands:

$Boll_t^{\mathrm{m}}(n)$ Moving average or median as the reference band
n: parameter to be modified

$Boll_t^{\mathrm{u}}(n)$	Upper Bollinger band	$Boll_t^{\mathrm{m}}(n) + s\sigma_t^2(n)$.
$Boll_t^{\mathrm{d}}(n)$	Lower Bollinger band	$Boll_t^{\mathrm{m}}(n) - s\sigma_t^2(n)$.

Each of the upper and lower Bollinger bands have the following parameters:

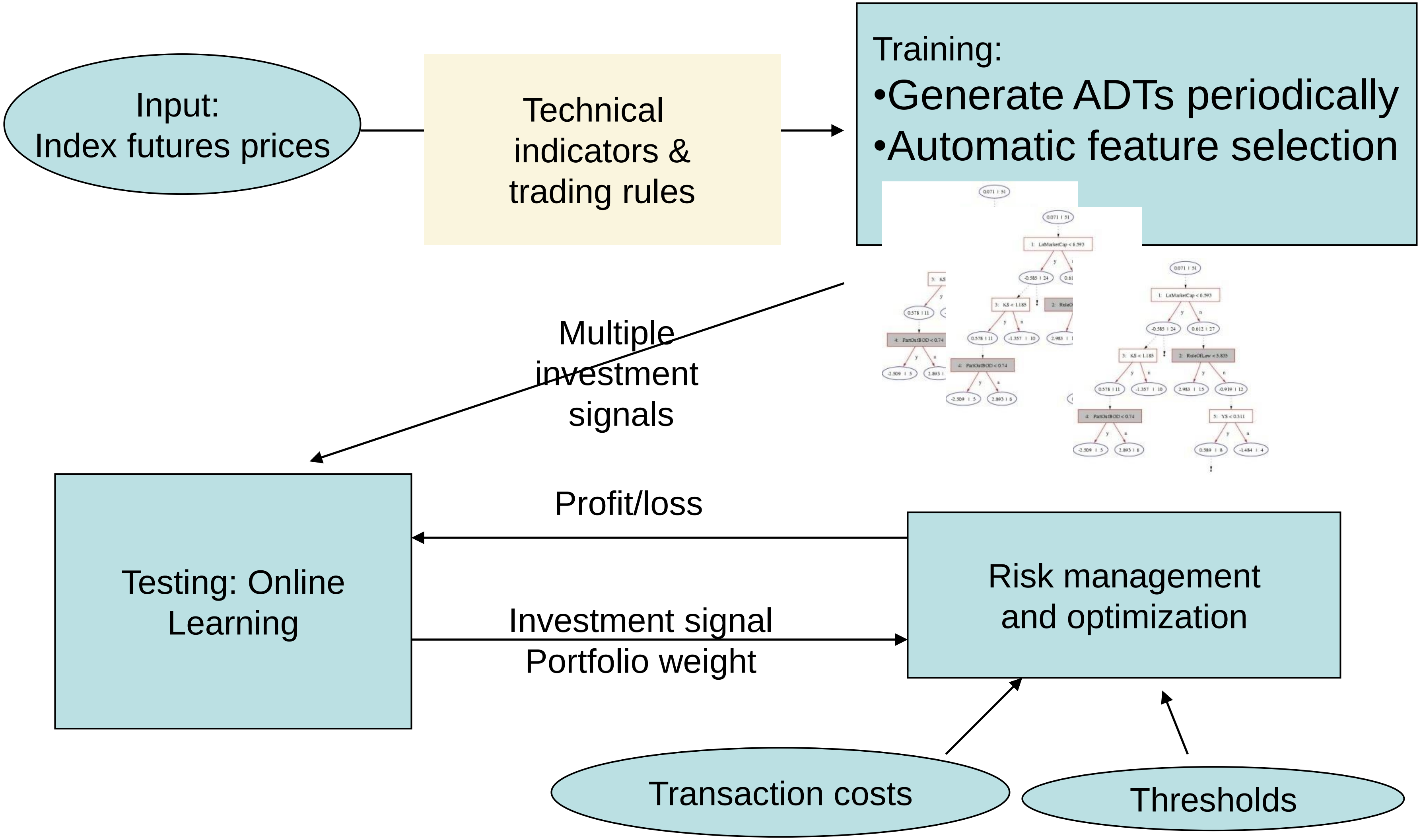
n: number of days used to calculate moving average

s: number of standard deviations above or below the reference band

At least two parameters to modify (s and n): trying 10 values for each parameter, there are 100 possible versions of Bollinger bands. Also each band may become an indicator itself.

How do we choose the optimal combination of technical indicators with the right parameters? Algorithm with capacity to learn → Machine learning methods such as boosting or Alternating Decision trees

Architecture of expert weight trading algorithm (Creamer and Freund 2010)



Components of expert weight trading algorithm

- Machine learning algorithm (logitboost, variation of boosting):
  - Select the best combination of rules derived from technical analysis indicators
  - Select the best parameters of the technical indicators: same indicator calculated several times and only most profitable versions are selected
- Online learning utility:
  - Combine the output of several ADTs and suggests a short or long position
  - More weight to recent experts
- Risk management layer:
  - Validate the trading signal when it exceeds a specified non-zero threshold $\text{if } |W_t| < \gamma_0, \text{ then } W_t = 0$
  - Restrict trading strategy when it is not profitable

Applying expert weight algorithm to futures trading (FESX & FDAX)

How?

- Aggregate order book at 10 seconds interval

Input: technical analysis and liquidity (spread, trade value, imbalance, etc.) indicators

Output: forecast of price trend

Process: Every day, trader process new information and take investment decision based on experts generated previous day

- During the day, new experts are generated and substitute older experts maintaining a max number of 25 experts

Evaluation:

- Transaction costs per futures contract: FESX: 0.3 EUR, FDAX: 0.5 EUR
- Compare results with Buy and Hold (B&H) or other learning algorithm using risk adjusted return (Sharpe ratio)
- Results aggregated daily for each of 22 trading days

Trading algorithm applied to Eurex futures

1) Logitboost: forecasts the direction of the futures price using experts (ADTs) which are implemented with Logitboost

Training using technical analysis and liquidity indicators (200 observations)

Logitboost combines technical and liquidity indicators and generates a new set of trading rules based on the market conditions

2) High frequency trading: (Example: partial market maker)

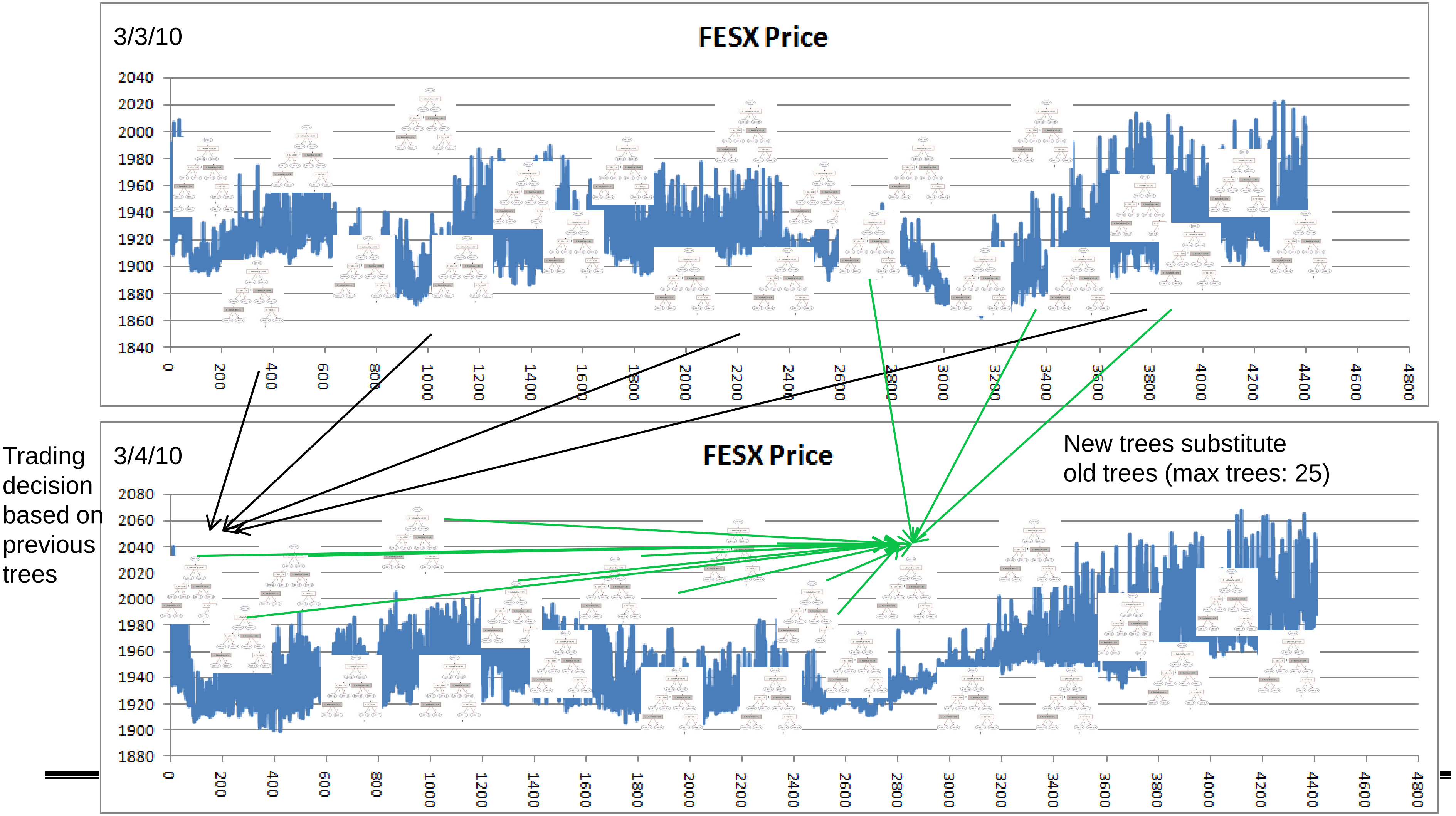
Every 200 observations (about half hour), trader sends a buy or sell limit order according to the combined forecast of the expert:

- If expected price trend is positive, send a buy limit order at prices lower than lowest bid price less transaction costs. If there is a short position, the size of the order is the short position. Otherwise, it is a futures contract
- If expected price trend is negative, send a sell limit order at prices higher than highest offer price plus transaction costs. If there is a long position, the size of the order is the long position. Otherwise, it is a futures contract

If the order is not 100% filled within a fixed period (i.e. 1 minute) of being issued, existent limit orders are cancelled, and limit orders are reissued according to current experts' forecast

Liquidate position at the end of the day

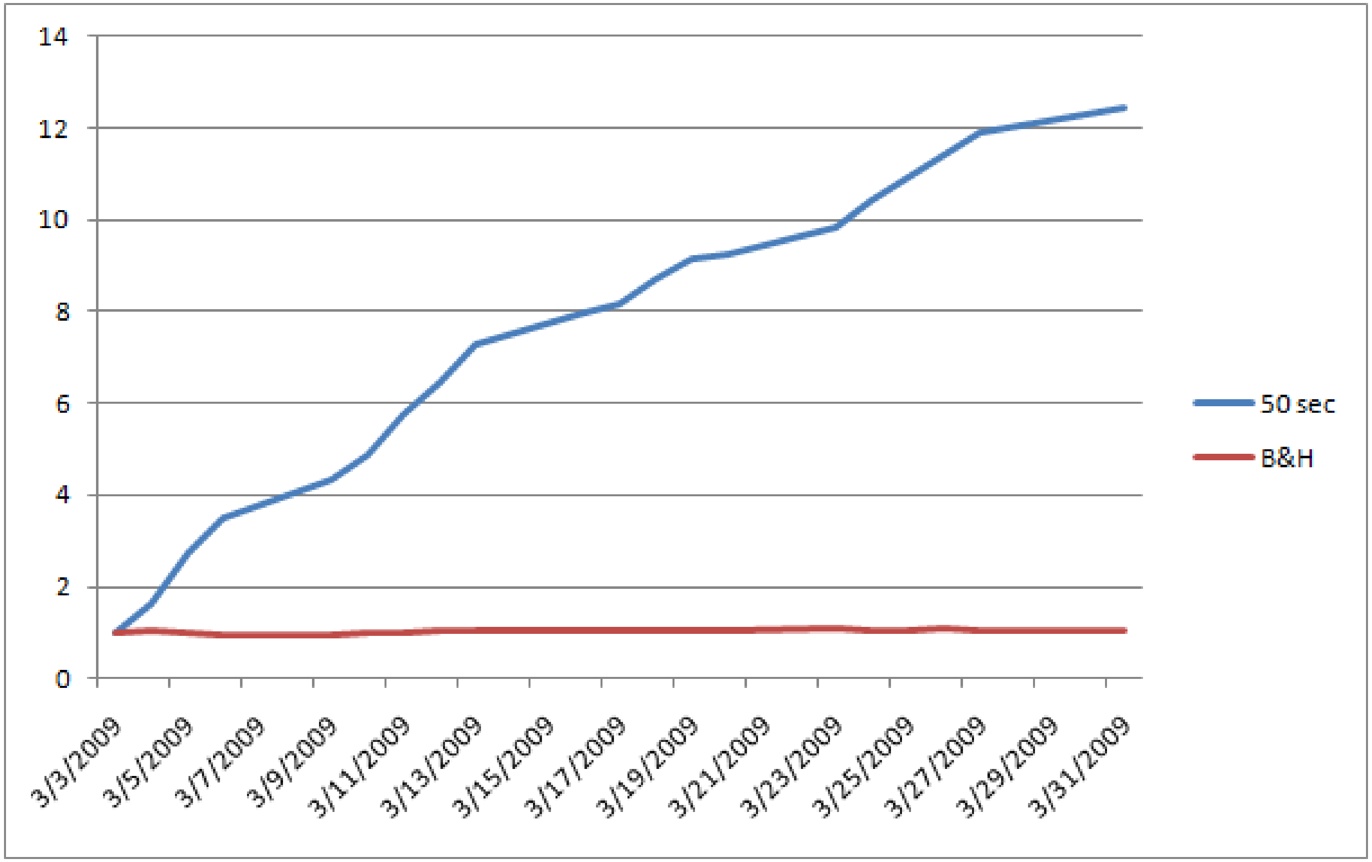
Dynamic of expert weight trading algorithm applied to intra-day Eurex data



Sharpe ratio for expert weight trading algorithm, March 2009: FESX & FDAX

Seconds btwn orders	FESX	FDAX
10	1.48	1.35
20	2.48	2.50
30	2.40	2.44
40	2.21	2.62
50	2.53	2.21
60	2.27	2.19
90	2.32	2.18
120	2.36	2.54
180	2.18	2.24
240	2.18	2.42
300	2.16	2.48
360	2.14	2.32
420	2.16	2.32
480	2.16	2.22
540	2.09	2.32
600	2.11	2.22
B&H	0.09	0.19

Results: Cumulative return for expert weight trading algorithm: FESX, March 2009



Comments

- Using boosting generates new trading rules & positive cumulative return:
  - Expert weight trading system:
    - Automatic feature selection: simultaneous calculation of the same feature with different parameters
    - Weighting algorithm: more weight to more profitable expert
    - Boosting or learning algorithm requires risk management rules:
      - reduce unprofitable trades that increase transaction costs
    - Appropriate for EURO STOXX 50® index future:
      - Highly liquid and volatile: offer profit opportunities

- Transforming technical indicators into ratios improve prediction

Comments

- High-frequency trading has a different market structure and experts behavior than daily or monthly trading:
  - Price patterns or indicators may not change much in very short periods of time unless that special events happen, so trader may need large number of experts to capture changes in market behavior
  - Reviewing trading order every fixed period (1-5 min.)

    & establishing minimum quality threshold reduces excessive trading