

# Digital Finance 3: Technology in Finance

## Lesson 29: Algorithmic Trading Concepts

FHGR

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**Algorithmic trading: where finance meets computer science.**

## Learning Objectives

By the end of this lesson, you will be able to:

- Classify different types of algorithmic trading strategies
- Design and execute backtesting frameworks
- Identify and avoid common backtesting pitfalls
- Understand overfitting in trading models
- Account for transaction costs and market impact
- Set realistic performance expectations

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**Overfitting produces excellent in-sample fit but poor out-of-sample predictions.**

# What is Algorithmic Trading?

## Definition:

- Automated execution based on rules
- No human intervention
- Computer algorithms make decisions
- Processes data faster than humans

## Market Share:

- US equities: 70-80% of volume
- Futures: 60-70%

## Key Advantages:

- Speed (microseconds)
- Consistency (no emotions)
- Backtesting capability
- Scalability

## Challenges:

- Overfitting to historical data
- Model decay (regime changes)
- Technology costs
- Regulatory scrutiny

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Clear definitions are essential for understanding complex technical concepts. [Source: DeFi Llama, DeFi Pulse 2024]

# Types of Strategies

## Execution Algorithms:

- VWAP, TWAP
- Minimize market impact
- Cost minimization

## Market Making:

- Provide liquidity
- Profit from spread
- High-frequency trading

## Statistical Arbitrage:

- Mean reversion
- Pair trading
- Market-neutral

## Momentum:

- Follow trends
- Breakout strategies
- Moving averages

## ML-Based:

- Prediction models
- Alternative data
- Classification/regression

## HFT:

- Ultra-short holding
- Latency arbitrage
- Co-location required

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Source: Academic AI/ML literature and industry adoption studies

## Steps:

- 1 Define strategy rules
- 2 Acquire historical data
- 3 Simulate trades
- 4 Calculate returns (net of costs)
- 5 Evaluate metrics
- 6 Iterate and refine

## Key Metrics:

- Total return
- Sharpe ratio (risk-adjusted)
- Maximum drawdown
- Win rate
- Profit factor

## Realistic Targets:

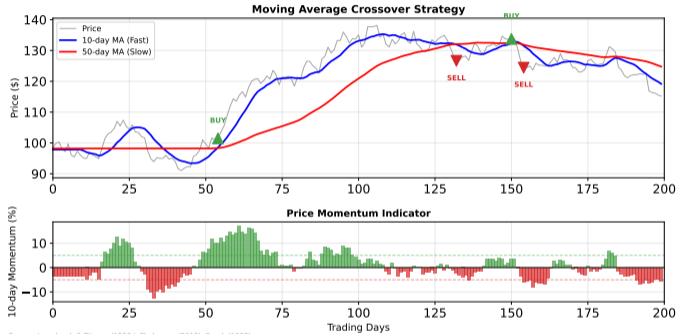
- Sharpe  $\geq$  1.5: Good
- Sharpe  $\geq$  2.0: Very good
- Sharpe  $\geq$  3.0: Exceptional (or overfitting?)

## Common Pitfalls:

- Look-ahead bias
- Survivorship bias
- Data snooping
- Ignoring costs
- Market impact
- Overfitting

**Warning:** Backtest performance usually overstates live performance.

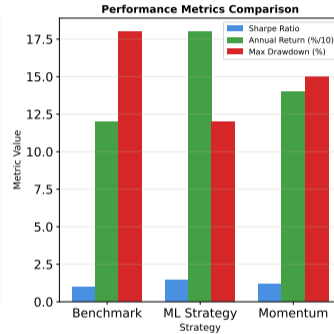
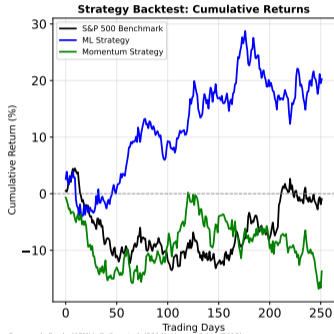
## Momentum Trading Strategy Analysis



Source: Jegadeesh & Titman (1993) Jof, Asness (2013), Brock (1992)

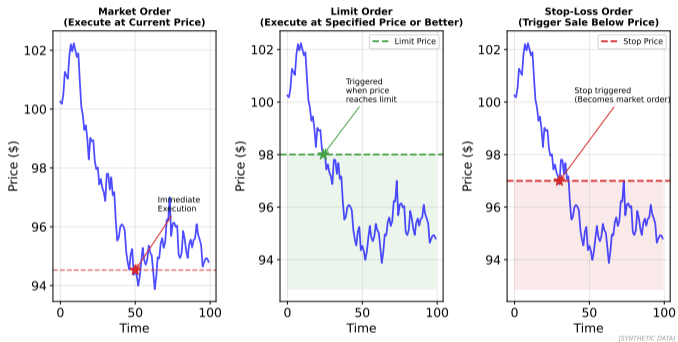
Momentum strategies buy winners and sell losers, exploiting short-term trends in asset prices.

## Algorithmic Trading Strategy Analysis



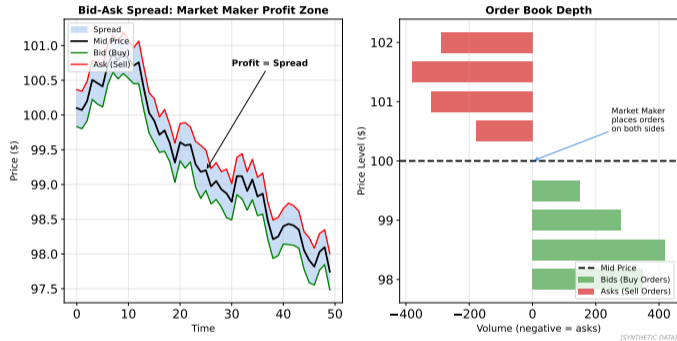
Backtesting reveals strategy performance metrics including returns, drawdowns, and Sharpe ratios.

## Order Types in Algorithmic Trading



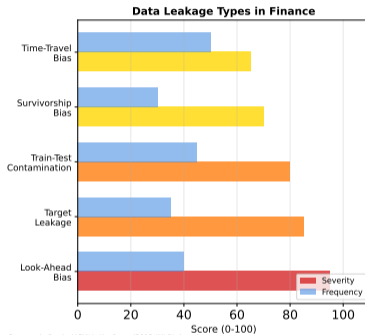
Different order types serve different execution objectives: market orders for speed, limit orders for price control.

## Market Making Strategy: Capturing the Spread



Market makers profit from bid-ask spreads while providing liquidity to the market.

## Data Leakage: A Critical ML Pitfall



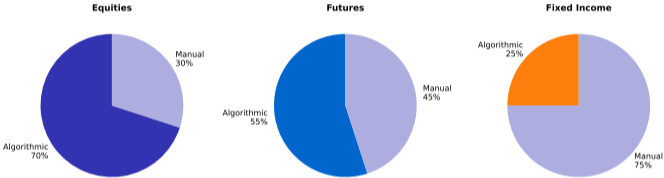
## Proper Time-Series Train/Test Split



Look-ahead bias occurs when future information leaks into historical simulations, inflating backtest results.

# Algorithmic Trading Market Share

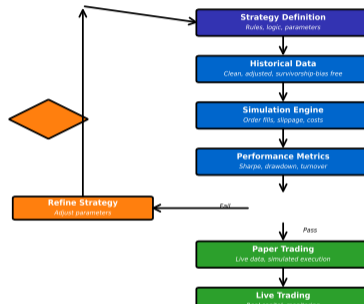
Algorithmic Trading Market Share by Asset Class



Source: quantifiedstrategies.com, JPMorgan Research (2023-2024)

Algorithmic trading now dominates equity markets, exceeding 80 percent of volume.

## Algorithmic Trading Backtesting Workflow



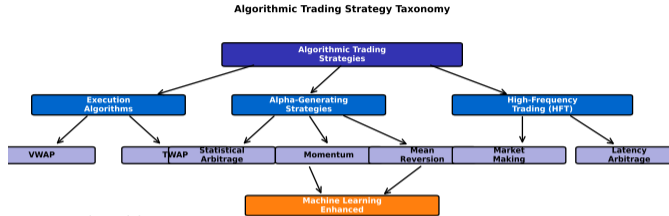
### Common Pitfalls:

- Lookahead bias
- Overfitting
- Survivorship bias
- Ignoring costs

Source: de Prado (Advances in Financial ML), Aronson (EBTA), Zipline

**Rigorous backtesting is essential but can mislead through overfitting and survivorship bias.**

# Algorithmic Strategy Types



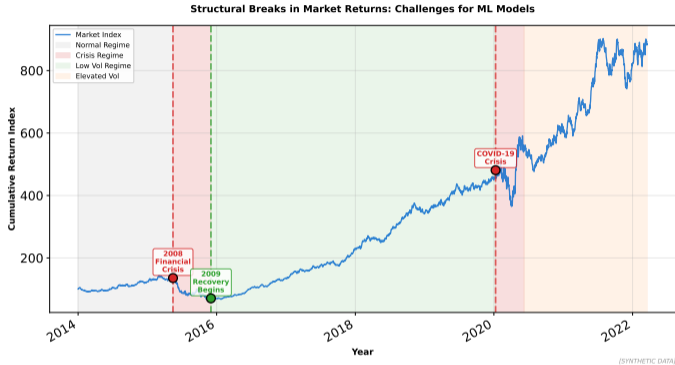
**Strategy Characteristics:**

- Execution: Minimize market impact
- Alpha-Generating: Exploit market inefficiencies
- HFT: Ultra-low latency, high turnover
- ML-Enhanced: Adaptive pattern recognition

Source: Kissell (Algo Trading), CFA Institute, Harris (Trading & Exchanges)

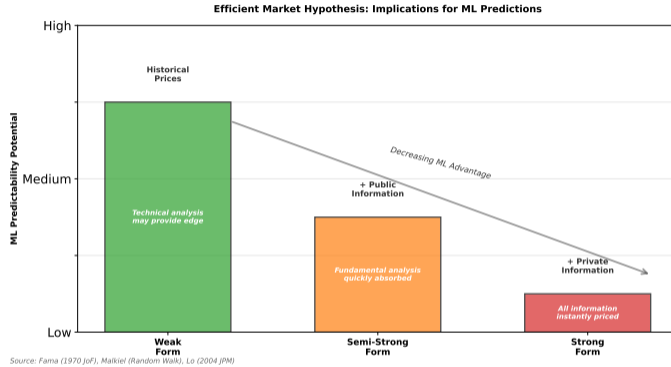
Algorithmic strategies range from high-frequency to fundamental trend-following.

# Structural Break Detection



Detecting regime changes is critical for adaptive trading strategies.

# Efficient Market Hypothesis Implications



EMH suggests that consistently beating the market through analysis is difficult.

## Key Takeaways:

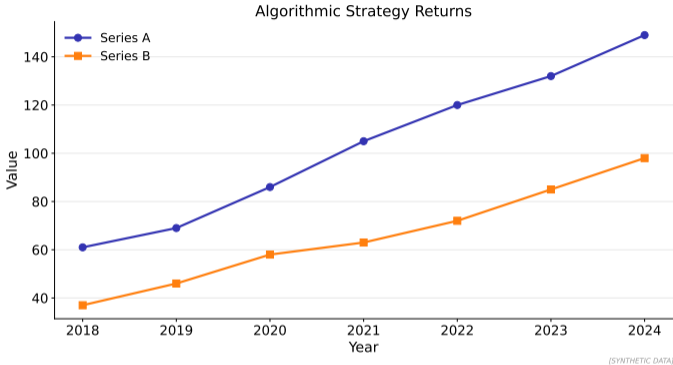
- Algorithmic trading dominates modern markets
- Many strategy types (execution, market making, stat arb, ML)
- Backtesting essential but has pitfalls
- Overfitting is the central danger
- Transaction costs matter (0.2-0.5% per round-trip)
- Realistic expectations: Alpha is scarce

**Next Lesson:** Credit Scoring and Risk Models

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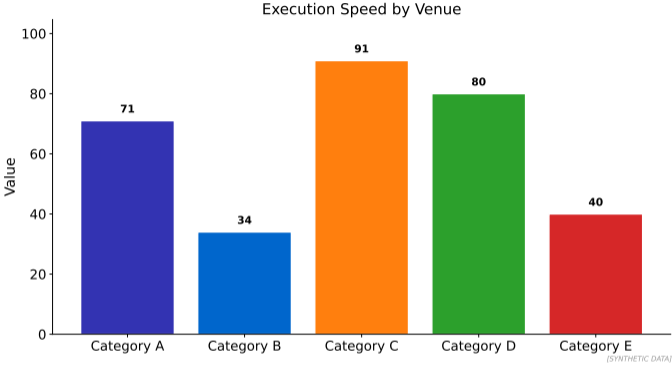
Survivorship bias inflates backtest returns by excluding failed companies from historical data.

# Algorithmic Strategy Performance



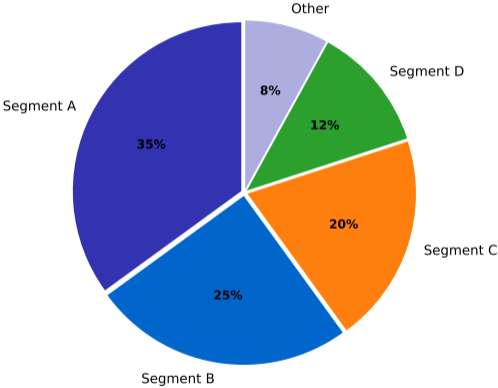
Strategy returns vary by market conditions and execution quality.

# Execution Speed by Venue



Latency differences impact execution quality.

## Algorithmic Trading Market Share



[SYNTHETIC DATA]

Market making and statistical arbitrage dominate volumes.