Dynamic trading strategies/systems

Strategy types, position sizing, and more

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TABLE 5.1 Rzepczynski (1999) convergent versus divergent financial worldviews.

Convergent	Divergent
Stationary, stable world	Nonstationary
World is knowable and static; structural knowledge	World is uncertain and dynamic; structural ignorance
Market participants generally form rational expectations; errors are random	Market participants form rational beliefs but may make mistakes and have biases
Markets adjust relatively to new information	Learning takes time; slower adjustment to information
Divergences from equilibrium are short lived	Divergence exists and may be dramatic from time to time
Fundamentals do not change dramatically in the short run	Fundamental changes are often unanticipated

Types of strategies

TABLE 5.2 Rzepczynski (1999) convergent versus divergent—trading/return behavior.

Convergent	Divergent
Strong sense of fair value	No prediction of fair value
Arbitrage trading, value trading, contrarian	Trend following, momentum
Negative Convexity	Positive Convexity
Profits made from reversion to the mean or long-term risk premiums	Profits made from the extremes, the mean fleeting events
Concave payoffs	Convex payoffs
Negatives skewness	Positive skewness

Mark S. Rzepczynski (1999), "Market Vision and Investment Styles: Convergent versus Divergent Trading", *The Journal of Alternative Investments*, pp. 77-82.

TABLE 5.3 **Rzepczynski (1999) convergent versus divergent trading by strategy type.**

Asset Class	Convergent	Divergent
Equity	Value, contrarian, arbitrage (pairs trading)	Momentum, growth
Fixed Income	Arbitrage, credit valuation	Interest rate directional
Hedge Funds	Arbitrage (fixed income, convertible) long short equity, sector funds, currency arbitrage	Managed futures, trend following, technical analysis

Four core decisions for a trading system

1. When to enter a position.
2. How large a position to take on.
3. How to get out of positions.
4. How much risk to allocate to different sectors and markets.

Greyserman and Kaminski (2014), “Trend Following with Managed Futures: The Search for Crisis Alpha”, John Wiley & Sons, Inc.

FIGURE 3.1 A schematic of trend following from data acquisition to position allocation.

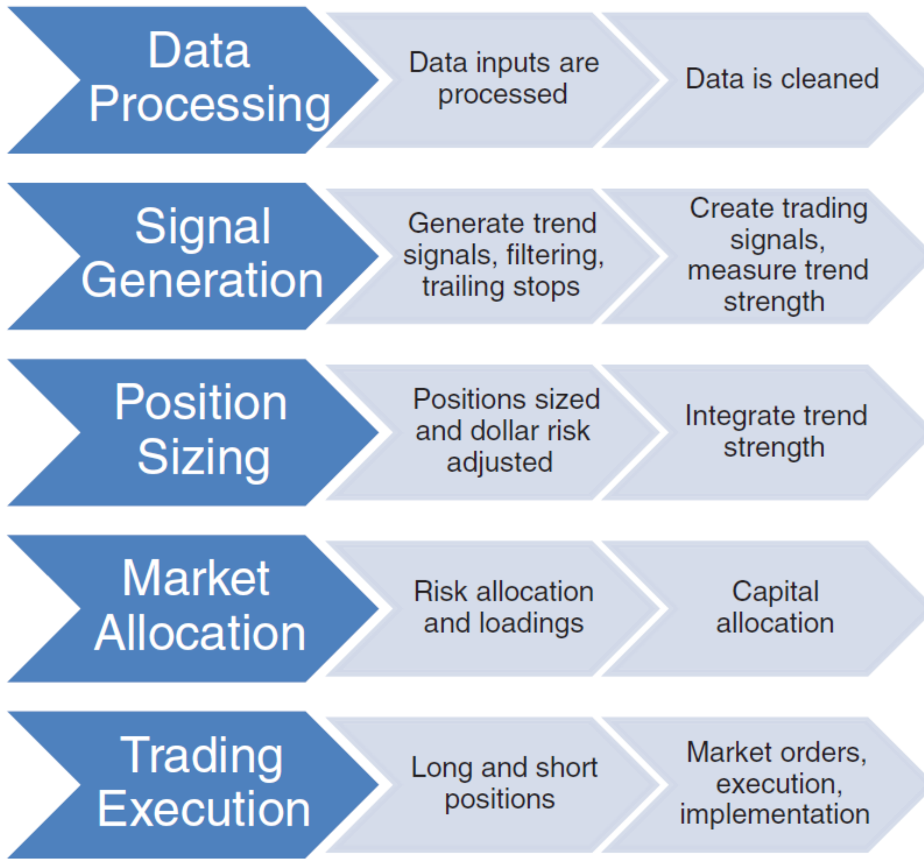

FIGURE 3.2 The five components of a trend following system.

Position Sizing

1. Trading systems allocate capital across asset classes/markets by systematically allocating risk or capital to individual markets.
2. Position sizing must consider the volatility of a particular market.

Remark: In your assignment, we don’t consider position sizing but apply unity exposure, i.e. either long or short one unit of asset.

1. **Position sizing based on dollar risk**[1]**:**

The nominal position (v) is equal to a **sizing function** times the **total adjusted dollar risk** times the nominal value of one contract.

$$v = s \times \underbrace{\frac{\theta \times c}{\sigma_K(\Delta P) \times PV}}_{\text{total adjusted dollar risk}} \times (PV \times P)$$

[1] Alternatively, we could consider average trading range (ATR) for each individual market. Average trading ranges are a simple way to incorporate actual trading volatility and volumes as opposed to using realized volatility. See Clenow (2013) for more details.

1. The sizing function (s) is a number between –1 and 1 ($s \in [-1,1]$). It determines the size and direction of a contract based on trading signals and trend strength.
2. The total adjusted dollar risk allocated is equal to the **allocated dollar risk** divided by the **futures contract dollar risk**. The allocated dollar risk is simply the risk loading (θ) times the allocated capital (c) per market. The futures contract dollar risk is the realized dollar risk ($\sigma_K(\Delta P)$ of each contract price over a lookback window of time (K) times the point value (PV)).

2. Position sizing based on volatility target:

Guilleminot et al. (2014) suggests the trend-based allocation for asset i at time t as

$$w_t^i = K_t \frac{Max\left(0, \mathrm{Trend}_t^i\right)}{\sigma_t^i},$$

where $Trend_t^i$ denotes the trend signal for asset i at time t, σ_t^i is the estimate of volatility for asset i at time t, and the parameter K_t is calculated by

$$K_t = \frac{\text{Target volatility}}{\sigma_t},$$

where σ_t is the estimate of portfolio volatility at time t with the weight for asset i equal to $\frac{Max\left(0, \mathrm{Trend}_t^i\right)}{\sigma_t^i}$.

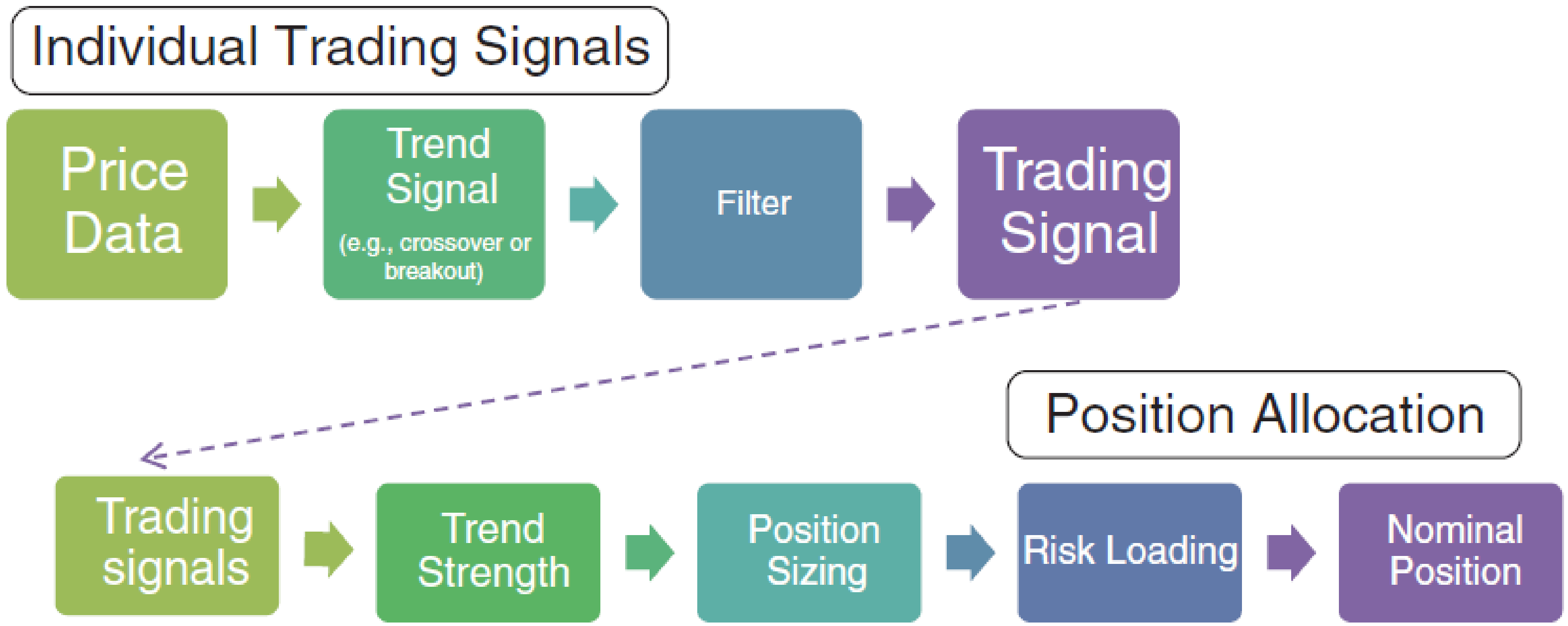

FIGURE 3.6 An example schematic of an integrated trend following system.

What's wrong with this design?

John Moody et al. (1998), “Performance Functions and Reinforcement Learning For Trading Systems and Portfolios”, *Journal of Forecasting,* Vol. 17, pp. 441-470.

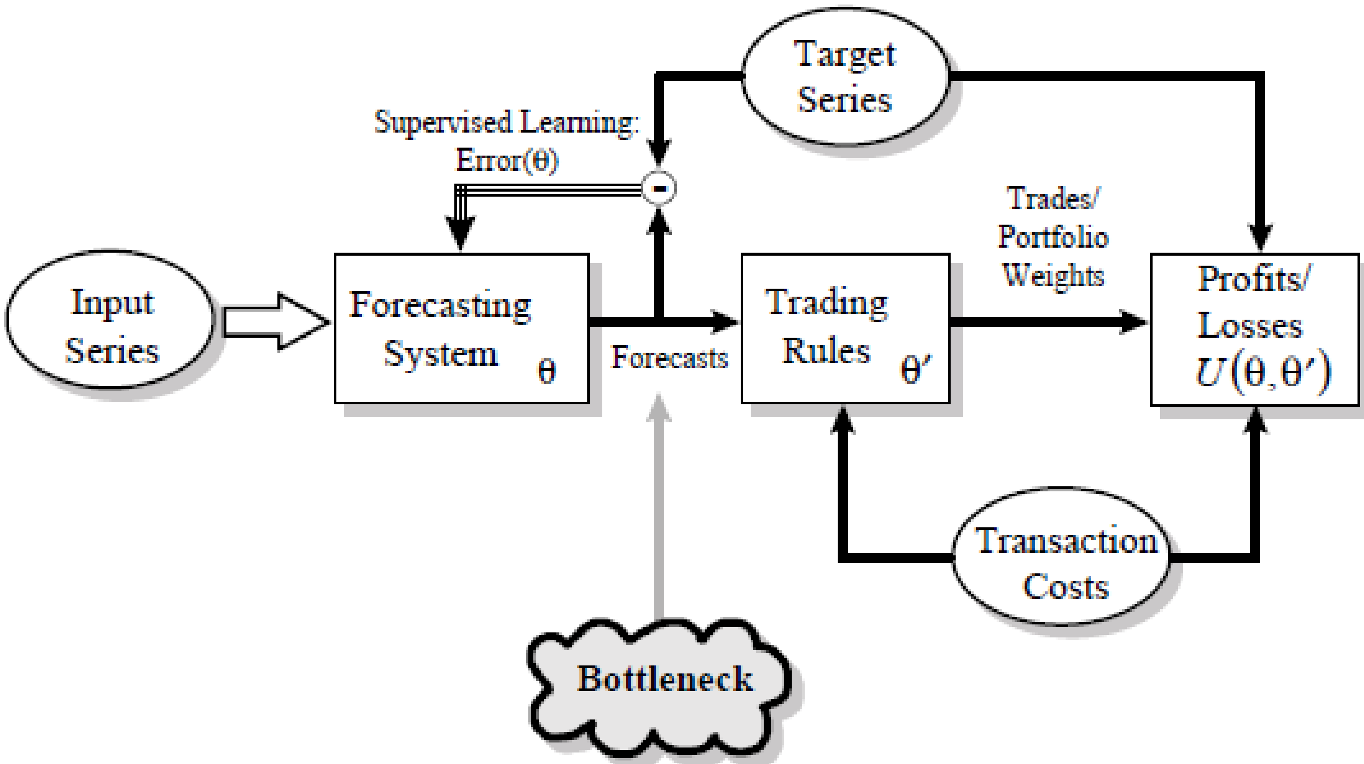

Figure 1: A trading system based on forecasts. The system includes a forecast module with adjustable parameters θ followed by a trading module with parameters θ'. Price forecasts for the target series are based on a set of input variables. The forecast module is trained by varying θ to minimize forecast error (typically mean squared error), which is an *intermediate quantity*. A more direct approach would be to simultaneously vary θ and θ' to maximize a measure of ultimate performance $U(\theta, \theta')$, such as trading profits, utility or risk-adjusted return. Note that the trading module typically does not make use of the inputs used by the forecast module, resulting in a loss of information or a *forecast bottleneck*. Performance of such a system is thus likely to be suboptimal.

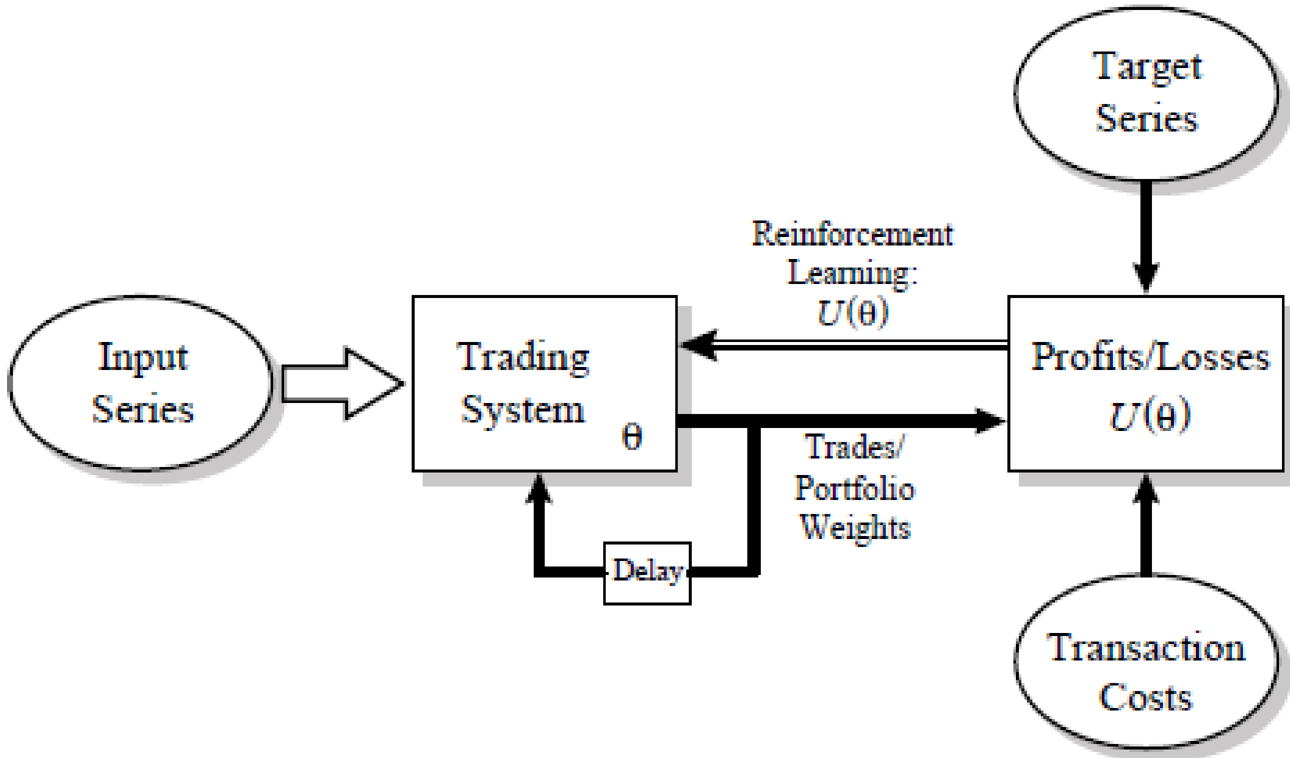

Figure 3: A trading system based on recurrent reinforcement learning, the approach taken in this paper. The system makes trading decisions directly based upon a set of input variables and the system state. A trading performance function $U(\theta)$, such as profit, utility or risk-adjusted return, is used to *directly optimize* the trading system parameters θ using reinforcement learning. The system is recurrent; the feedback of system state (current positions or portfolio weights) enables the trading system to learn to correctly incorporate transactions costs into its trading decisions. In comparison to the systems in Figures 1 and 2, no intermediate steps such as making forecasts or labelling desired trades are required.

Research project of past graduate student

Dynamic Asset Allocation for Pairs Trading

https://www.cs.toronto.edu/~francohtlin/dynamic-asset-allocation.pdf

Unfinished discussion

1. Reinforcement learning/Dynamic programming
2. Signal generation (Data-driven/ value-based)
3. Long-run return predictability
4. Else (frequency, cost, risk management)