

Multi-Strategy Trading Utilizing Market Regimes

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- These are “model-based” methods. So, one makes assumptions (e.g., known expected returns) that may turn out to be troublesome.
- This issue spurred research into “model-free” approaches.

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- Universal portfolio (Cover 1991) - Sequential portfolio allocation to match the best constantly rebalanced portfolio in hindsight (for an **arbitrary market process**).
- Many extensions and follow-on work: multiplicative updates (Helmbold et al. 1998), efficient online computation (Kalai et al. 2002), Anticor (Borodin et al. 2004), kernel-weighted allocation (Györfi et al. 2006).

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- We seek online procedures that also allow us to utilize context in the spirit of (non-parametric) statistics.

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- Devise online algorithm for dynamically rebalancing portfolio, shaped by contextual information.

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- *Regimes*: Characterize context by relative profitability of primitive strategies.
 - Good trading strategies exploit **recurring market dynamics** that can be **more prevalent in some time periods than in others**.
 - Trends depend on hard to model latent variables - we seek alternate state description in an action-oriented representation.

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But, it is helpful to differentiate the **static** structure implied by the qualitative strategy from the **dynamic** evolution of regimes.

Portfolio Allocation Algorithm: A Template

Three major steps:

- (Optional) Use historical data to **infer** set of regimes, i.e., relative order between strategies.

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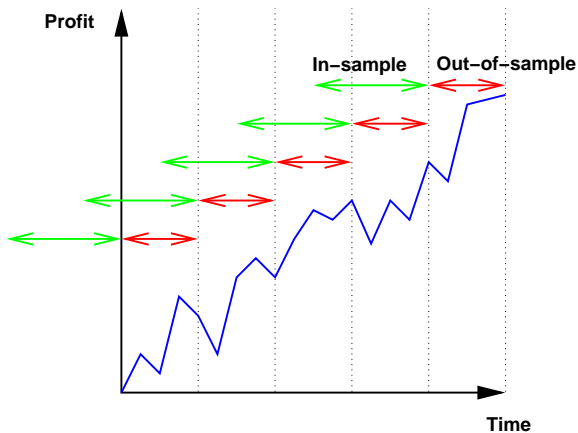
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- **In-Sample**: Identify the order (by performance) over regimes within a moving window, i.e., **estimate** current context.

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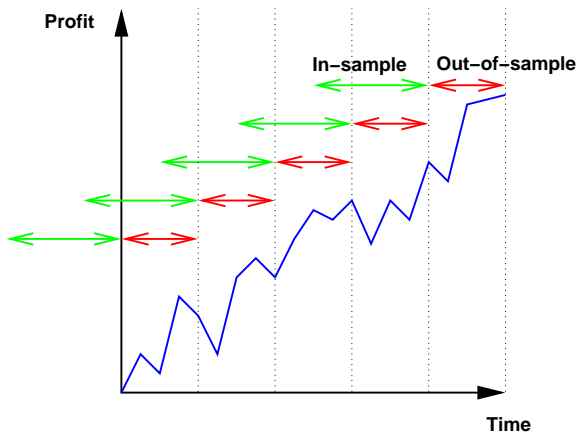
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- **Out-Sample**: **Allocate** working capital assuming persistence of the identified in-sample context.

Simplest Instantiation: Trade with Best In-Sample Strategy

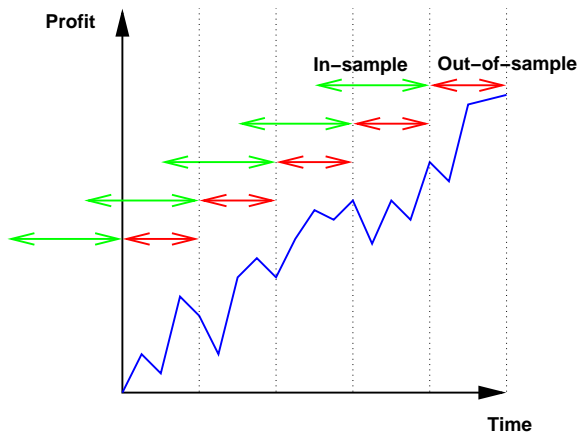


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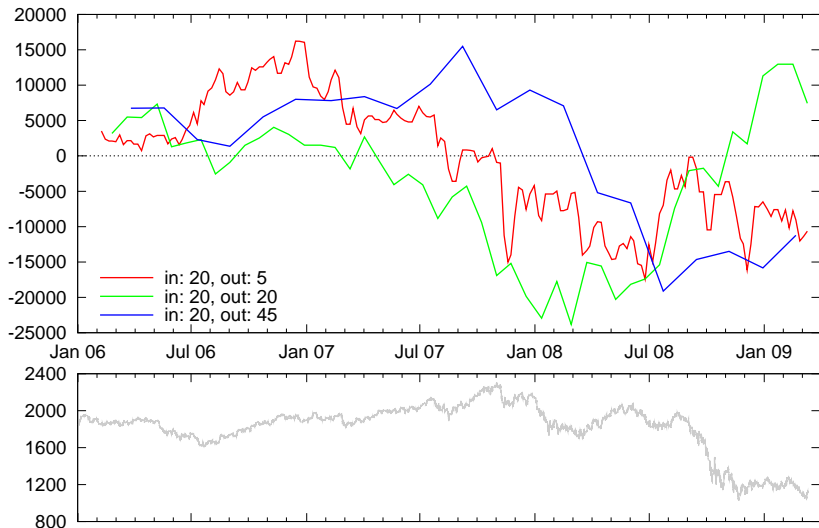
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Simplest Instantiation: Trade with Best In-Sample Strategy



- **In:** Identify best quantitative strategy
- **Out:** Allocate capital to the best in-sample strategy

Performance: Trading with Best In-Sample Strategy



Observations: Trading with Best In-Sample Strategy

Can be profitable. However,

- Sensitivity to parameter choice, e.g., window size.
- Need fine-grained trading to follow changing trends.
- Wasteful chatter between different strategies.
 - Diversification could help solve some of these problems.

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This is more diversified, but tends not to suffice.

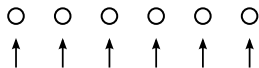
– we will see a few empirical results later in this presentation.

Regimes - Layered Graph of Strategies

- Regimes: weighted groups of strategies exhibiting correlated behaviour according to a fitness function

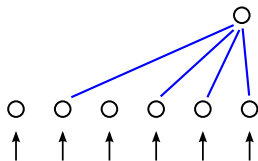
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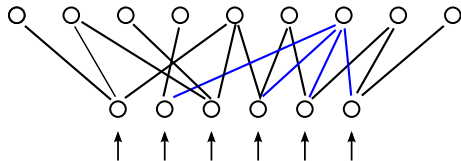
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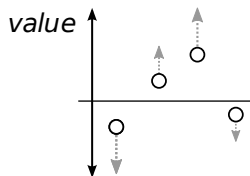
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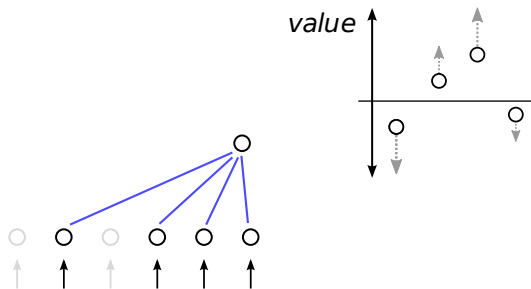
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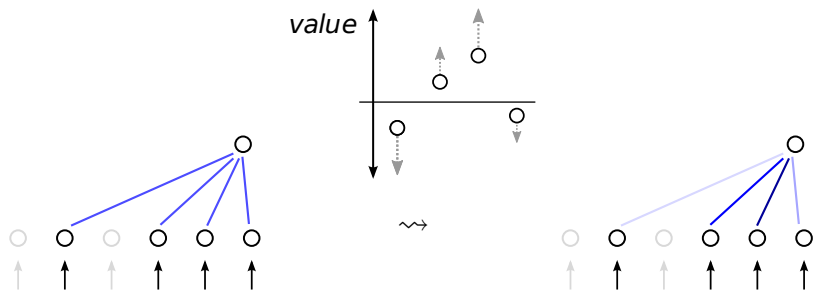
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The effective number of regimes may be significantly smaller than the number of underlying strategies.

- Dimensionality reduction would aid the state identification step
 - Previous instantiations may be considered special cases
- Possible to build predictive models in a space that is different from standard latent variable time series models.

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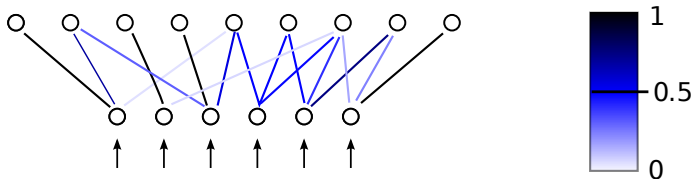
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 - Find significantly correlated events among possible combinations of events e.g. using permutation tests

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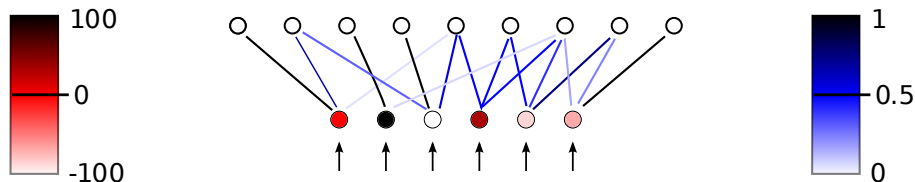
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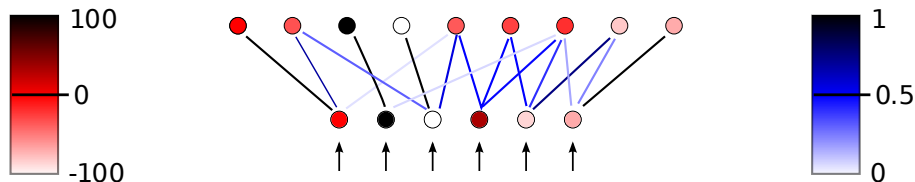
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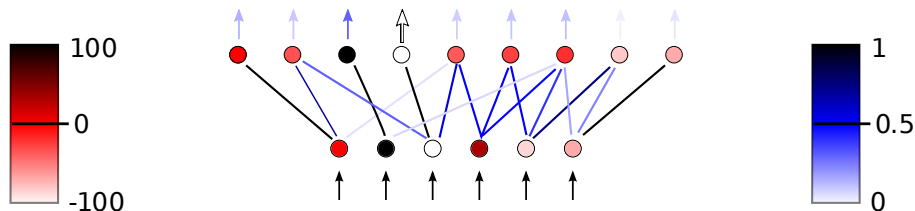
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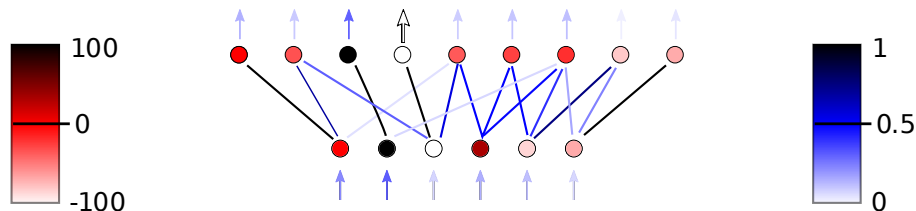
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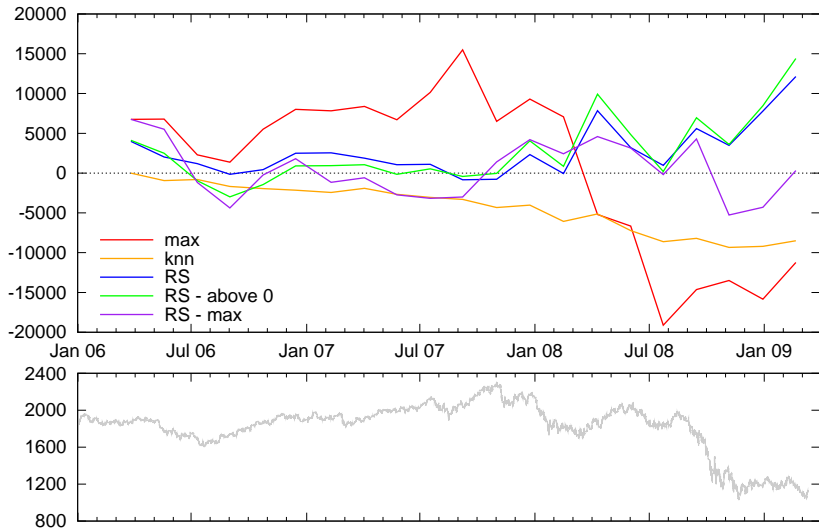
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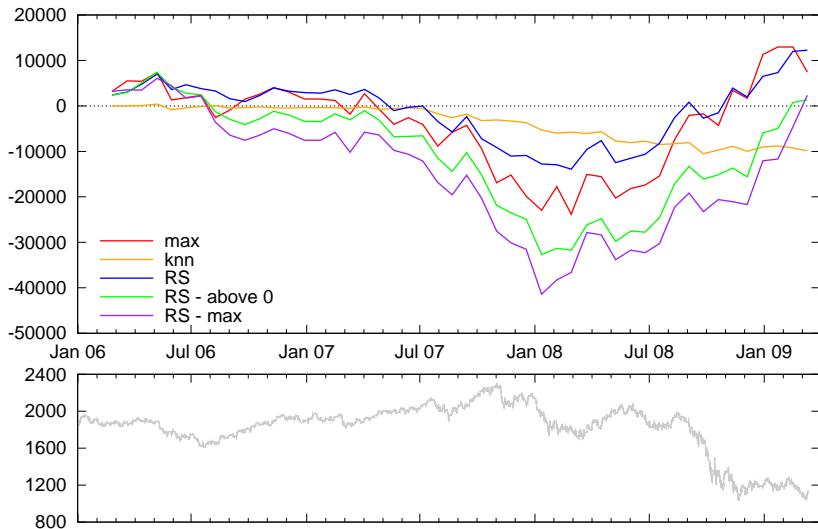
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- Out-of-sample period (Trading): Multiplicative weight update for allocation between regimes



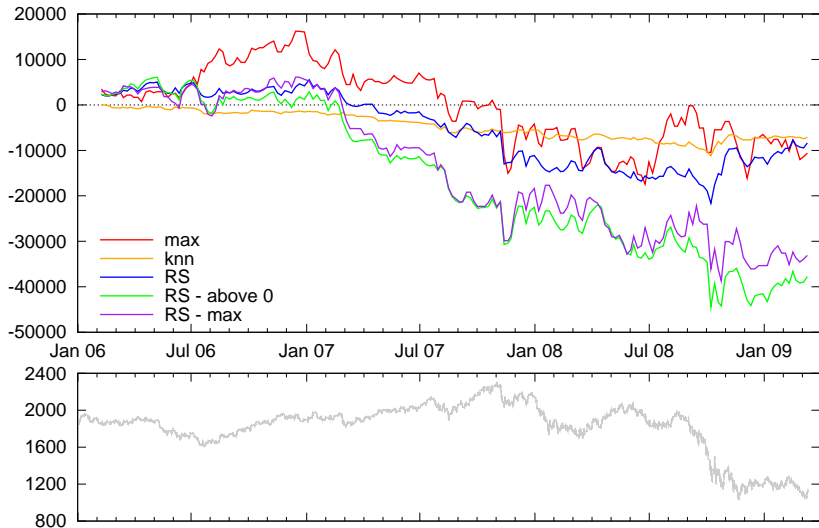
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 - Structure in this space (e.g., low-dimensional regime subspaces) can be exploited to devise more efficient strategies.

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