Optimal portfolio strategies under partial information with expert opinions

Ralf Wunderlich

Brandenburg University of Technology Cottbus, Germany

Joint work with Rüdiger Frey

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Agenda

1. Dynamic Portfolio Optimization
2. Partial Information and Expert Opinions
3. Optimization for Power Utility
4. Approximation of the Optimal Strategy

Dynamic Portfolio Optimization

Initial capital $x_0 > 0$

Horizon $[0, T]$

Aim maximize expected utility of terminal wealth

Problem find an optimal investment strategy

How many shares

of **which** asset

have to be held **at which time** by the portfolio manager **?**

Market model continuously tradable assets

drift depends on unobservable finite-state Markov chain

investor only observes stock prices and

expert opinions

Classical Black-Scholes Model of Financial Market

$(\Omega, \mathbb{G} = (\mathcal{G}_t)_{t\in[0,T]}, P)$ filtered probability space

Bond $S_t^0 = e^{rt}$, r risk-free interest rate

Stocks prices $S_t = (S_t^1, \dots, S_t^n)^\top$, returns $dR_t^i = \frac{dS_t^i}{S_t^i}$

$dR_t = \mu\, dt + \sigma\, dW_t$

$\mu \in \mathbb{R}^n$ average stock return, drift

$\sigma \in \mathbb{R}^{n\times n}$ volatility

W_t n-dimensional Brownian motion

parameters μ and σ are constant and known

Generalization time-dependent (non-random) parameters μ, σ, r

Portfolio

Initial capital $X_0 = x_0 > 0$

Wealth at time t invested in $X_t = X_t(\underbrace{h_t^0}_{\text{bond}} + \underbrace{h_t^1}_{\text{stock 1}} + \ldots + \underbrace{h_t^n}_{\text{stock n}})$

h_t^k fractions of wealth invested in asset k

Strategy $\boldsymbol{h_t = (h_t^1, \ldots, h_t^n)^\top}$

Self financing condition (assume $r = 0$ for simplicity) $\Rightarrow$

Wealth equation

X_t satisfies **linear SDE** with initial value x_0

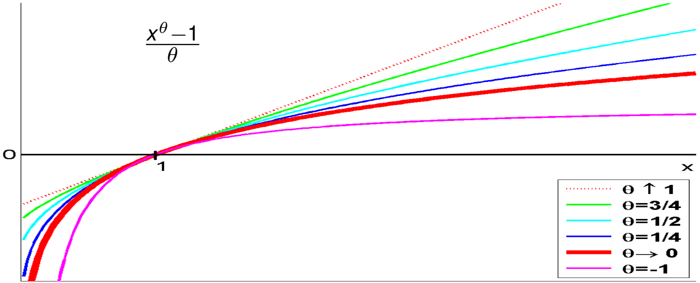
$$dX_t^{(h)} = X_t^{(h)} \boldsymbol{h_t^\top} (\mu\, dt + \sigma dW_t)$$
$$X_0^{(h)} = x_0$$

Utility Function

$U : [0, \infty) \to \mathbb{R} \cup \{-\infty\}$ strictly increasing and concave

Inada conditions $\lim_{x \downarrow 0} U'(x) = \infty$ and $\lim_{x \uparrow \infty} U'(x) = 0$

$$U(x) = \begin{cases} \frac{x^\theta}{\theta} & \text{for } \theta \in (-\infty, 1) \setminus \{0\} \quad \text{power utility} \\ \log x & \text{for } \theta = 0 \quad \text{log-utility} \end{cases}$$



Optimization Problem

Wealth $dX_t^{(h)} = X_t^{(h)} h_t^\top (\mu\, dt + \sigma dW_t), \quad X_0^{(h)} = x_0$

Admissible Strategies $\mathcal{H} = \{(h_t)_{t\in[0,T]} \mid h_t \in \mathbb{R}^n, \; E\big[\exp\{\int_0^T \|h_t\|^2 dt\}\big] < \infty \; \}$

Reward function $v(t,x,h) = E_{t,x}[\, U(X_T^{(h)})\,] \qquad \text{for} \quad h \in \mathcal{H}$

Value function $V(t,x) \; = \sup_{h\in\mathcal{H}} \; v(t,x,h)$

Find optimal strategy $h^* \in \mathcal{H}$ such that $V(0,x_0) = v(0,x_0,h^*)$

Solution optimal fractions of wealth $h_t^* = \dfrac{1}{1-\theta}(\sigma\sigma^\top)^{-1}\mu = \text{const}$

Merton (1969,1973)

using methods from dynamic programming

Drawbacks of the Merton Strategy

Sensitive dependence of investment strategies on the **drift** μ of assets

Drift **is hard to estimate empirically**

need data over long time horizons

(other than volatility estimation)

is not constant

depends on the state of the economy

Non-intuitive strategies

for constant fraction of wealth $\in (0, 1)$ $\Longrightarrow$

sell stocks when prices increase

buy stocks when prices decrease

$\Longrightarrow$ **Model drift as stochastic process, not directly observable**

Models With Partial Information on the Drift

Drift depends on an additional "source of randomness"

$\mu = \mu_t = \mu(\boldsymbol{Y_t})$ with factor process Y_t

Investor is not informed about factor process Y_t, he only observes

Stock prices S_t or equivalently stock returns R_t

Expert opinions news, company reports

recommendations of analysts or rating agencies

own view about future performance

$\Longrightarrow$ Model with **partial information**

Problem Investor needs to "learn" the drift from observable quantities

Find an estimate or **filter** for $\mu(Y_t)$

Linear Gaussian Model

Lakner (1998), Nagai, Peng (2002), Brendle (2006)

Drift $\mu(Y_t) = Y_t$ is a mean-reversion process

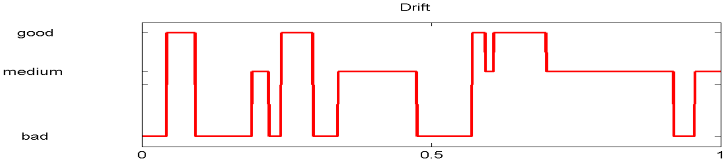
$$dY_t = \alpha(\overline{\mu} - Y_t)dt + \beta dW_t^1$$

where W_t^1 is a Brownian motion (in)dependent of W_t

Models With Partial Information on the Drift (cont.)

Hidden Markov Model (HMM)

Sass, Haussmann (2004), Rieder, Bäuerle (2005), Nagai, Rungaldier (2008)



Factor process Y_t finite-state Markov chain, independent of W_t

state space $\{e_1, \dots, e_d\}$, unit vectors in $\mathbb{R}^d$

states of drift $\mu(Y_t) = MY_t$ where $M = (\mu_1, \dots, \mu_d)$

generator or rate matrix $Q \in \mathbb{R}^{d \times d}$

diagonal: $Q_{kk} = -\lambda_k$ exponential rate of leaving state k

conditional transition prob. $P(Y_t = e_l \mid Y_{t-} = k, Y_t \neq Y_{t-}) = Q_{kl}/\lambda_k$

initial distribution $(\pi^1, \dots, \pi^d)^\top$

HMM Filtering

Returns $dR_t = \frac{dS_t}{S_t} = \mu(Y_t)\,dt + \sigma\,dW_t$ observations

Drift $\mu(Y_t) = M\,Y_t$ non-observable (hidden) state

Investor Filtration $\mathbb{F} = (\mathcal{F}_t)_{t\in[0,T]}$ with $\mathcal{F}_t = \sigma(S_u :\ u \le t) \subset \mathcal{G}_t$

Filter $p_t^k := P(Y_t = e_k | \mathcal{F}_t)$

$$\widehat{\mu(Y_t)} := E[\mu(Y_t)|\mathcal{F}_t] \quad = \mu(p_t) \;=\; \sum_{j=1}^{d} p_t^j\,\mu_j$$

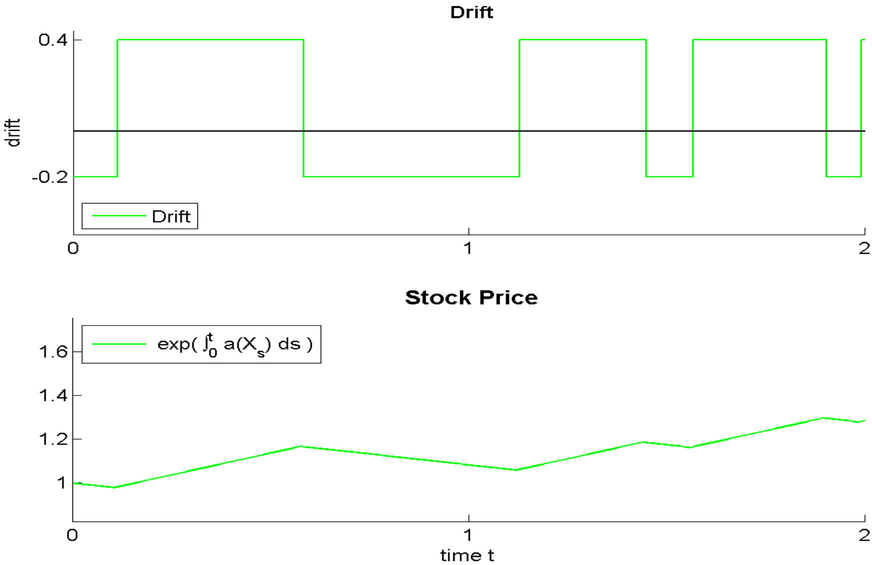
Innovations process $B_t := \sigma^{-1}\big(\ R_t - \int_0^t \widehat{\mu(Y_s)}ds\ \big)$ is an $\mathbb{F}$-BM

HMM filter Liptser, Shiryaev (1974), Wonham (1965), Elliot (1993)

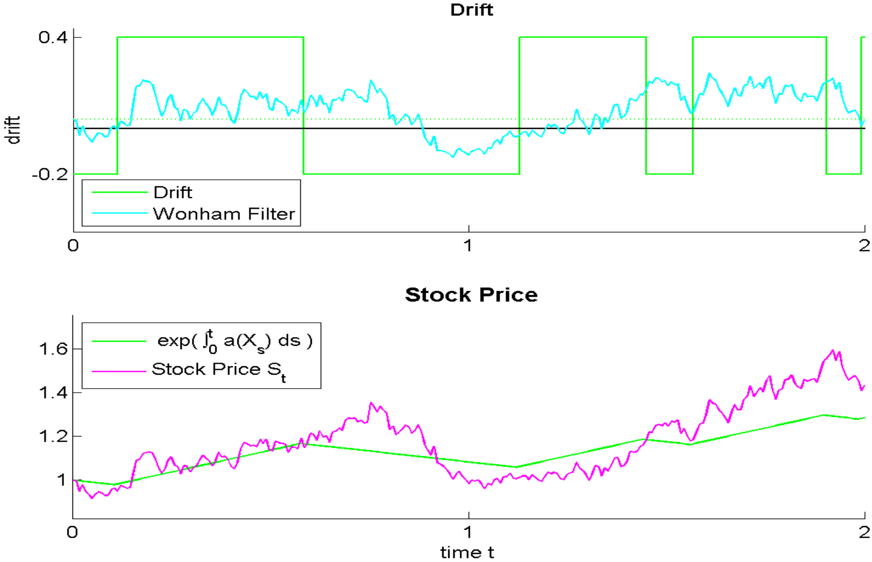
$$\begin{aligned} p_0^k &= \pi^k \\ dp_t^k &= \sum_{j=1}^{d} Q^{jk} p_t^j dt + \beta_k(p_t)^\top dB_t \end{aligned}$$

$$\text{where} \quad \beta_k(p) = p^k \sigma^{-1}\Big(\mu_k - \sum_{j=1}^{d} p^j \mu_j\Big)$$

HMM Filtering: Example



HMM Filtering: Example



Expert Opinions

- **Academic literature:** drift is driven by unobservable factors
  Models with partial information, apply filtering techniques
  - Linear Gaussian models
  - Hidden Markov models
- **Practitioners** use static **Black-Litterman model**
  Apply Bayesian updating to combine
  subjective views (such as “asset 1 will grow by 5%”)
  with empirical or implied drift estimates
- Present paper combines the two approaches
  consider **dynamic** models with partial observation
  including **expert opinions**

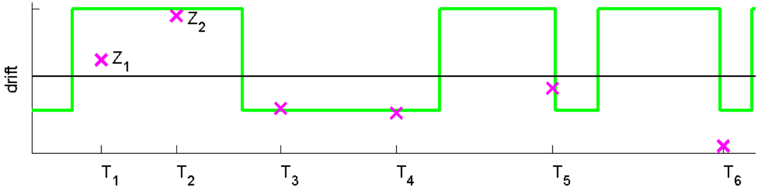
Expert Opinions

Modelled by marked point process $I = (T_n, Z_n) \sim I(dt, dz)$

- At random points in time $T_n \sim \text{Poi}(\lambda)$ investor observes r.v. $Z_n \in \mathcal{Z}$
- Z_n depends on current state Y_{T_n}, density $f(Y_{T_n}, z)$
  (Z_n) cond. independent given $\mathcal{F}_T^Y = \sigma(Y_s : s \in [0, T])$

Examples

- Absolute view: $Z_n = \mu(Y_{T_n}) + \sigma_\varepsilon \varepsilon_n$, (ε_n) i.i.d. $N(0,1)$
  The view "S will grow by 5%" is modelled by $Z_n = 0.05$
  σ_ε models confidence of investor



- Relative view (2 assets): $Z_n = \mu_1(Y_{T_n}) - \mu_2(Y_{T_n}) + \widetilde{\sigma}_\varepsilon \varepsilon_n$

Investor filtration $\mathbb{F} = (\mathcal{F}_t)$ with $\mathcal{F}_t = \sigma(S_u : u \le t;\ (T_n, Z_n) : T_n \le t)$

HMM Filtering - Including Expert Opinions

Extra information has no impact on filter p_t between 'information dates' T_n

Bayesian updating at $t = T_n$:

$$p^k_{T_n} \;\propto\; p^k_{T_n-}\, f(e_k, Z_n) \qquad \text{recall: } f(Y_{T_n}, z) \text{ is density of } Z_n \text{ given } Y_{T_n}$$

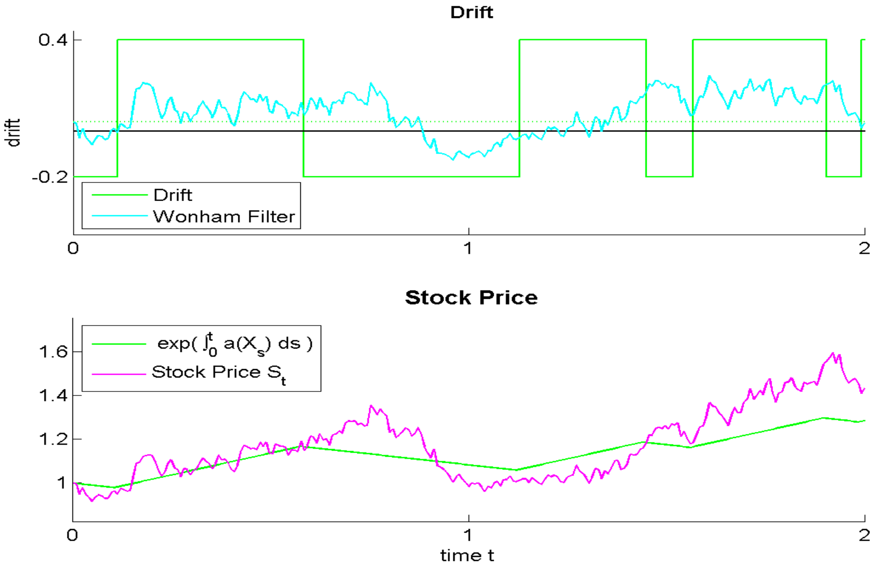
$$\text{with normalizer} \quad \sum_{j=1}^{d} p^j_{T_n-} f(e_j, Z_n) \;=:\; \bar{f}(p_{T_n-}, Z_n)$$

HMM filter

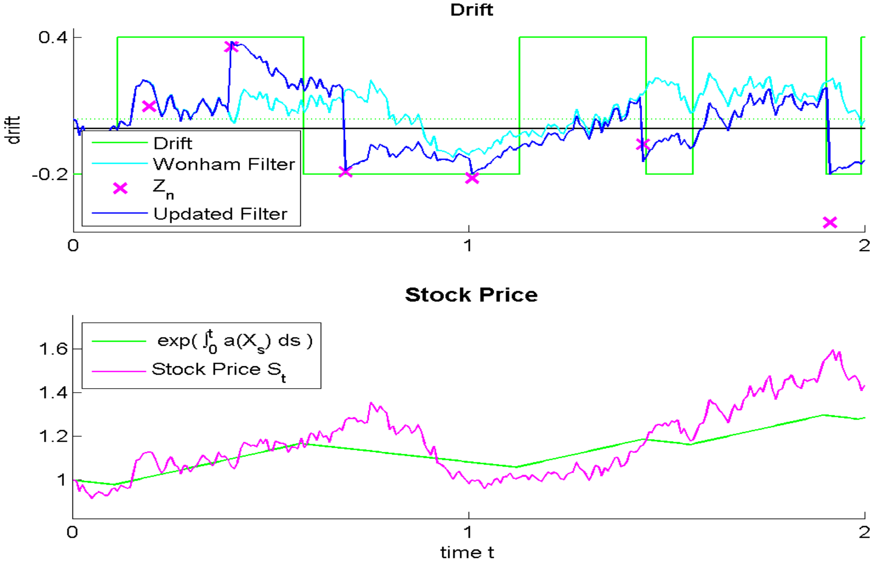
$$\begin{aligned} p^k_0 &= \pi^k \\ dp^k_t &= \sum_{j=1}^{d} Q^{jk} p^j_t dt + \beta_k(p_t)^\top dB_t + \boldsymbol{p^k_{t-} \int_{\mathcal{Z}} \left(\frac{f(e_k,z)}{\bar{f}(p_{t-},z)} - 1 \right) \widetilde{I}(dt \times dz)} \end{aligned}$$

Compensated measure $\widetilde{I}(dt \times dz) := I(dt \times dz) - \underbrace{\lambda dt \sum_{k=1}^{d} p^k_{t-} f(e_k, z)\, dz}_{\text{compensator}}$

Filter: Example



Filter: Example



Optimization Problem Under Partial Information

Wealth $\quad dX_t^{(h)} = X_t^{(h)}\, h_t^\top \,(\boldsymbol{\mu(Y_t)}\, dt + \sigma dW_t), \quad X_0^{(h)} = x_0$

Admissible Strategies $\quad \mathcal{H} = \{(h_t)_{t\in[0,T]} \mid h_t \in K \subset \mathbb{R}^n$ with K compact, h is $\mathbb{F}$-adapted $\}$

Reward function $\quad v(t,x,h) = E_{t,x}[\, U(X_T^{(h)})\,] \qquad$ for $\quad h \in \mathcal{H}$

Value function $\quad V(t,x) \; = \sup_{h\in\mathcal{H}} \; v(t,x,h)$

Find optimal strategy $h^* \in \mathcal{H}$ such that $V(0,x_0) = v(0,x_0,h^*)$

Reduction to an OP Under Full Information

Consider augmented state process (X_t, p_t)

Wealth $$dX_t^{(h)} = X_t^{(h)} \, h_t^\top \, \big(\underbrace{\widehat{\mu(Y_t)}}_{= M p_t} \, dt + \sigma \, d\boldsymbol{B_t} \big), \qquad X_0^{(h)} = x_0$$

Filter $$dp_t^k = \sum_{j=1}^{d} Q^{jk} p_t^j dt + \beta_k(p_t)^\top dB_t$$

$$+ p_{t-}^k \int_{\mathcal{Z}} \left(\frac{f(e_k, z)}{\bar{f}(p_{t-}, z)} - 1 \right) \widetilde{I}(dt \times dz), \qquad p_0^k = \pi^k$$

Reward function $$v(t, x, p, h) = E_{t,x,p}[\, U(X_T^{(h)}) \,] \qquad \text{for} \quad h \in \mathcal{H}$$

Value function $$V(t, x, p) \; = \sup_{h \in \mathcal{H}} \; v(t, x, p, h)$$

Find $h^* \in \mathcal{H}(0)$ such that $V(0, x_0, \pi) = v(0, x_0, \pi, h^*)$

Logarithmic Utility

$$U(X_T^{(h)}) = \log(X_T^{(h)}) = \log x_0 + \int_0^T \left(h_s^\top \widehat{\mu(Y_s)} - \frac{1}{2} h_s^\top \sigma\sigma^\top h_s \right) ds + \int_0^T h_s^\top \sigma dB_s$$

$$E[U(X_T^{(h)})] = \log x_0 + E\left[\int_0^T \left(h_s^\top \widehat{\mu(Y_s)} - \frac{1}{2} h_s^\top \sigma\sigma^\top h_s \right) ds \right] + 0$$

Optimal Strategy

$$h_t^* = (\sigma\sigma^\top)^{-1} \widehat{\mu(Y_t)}.$$

Certainty equivalence principle

h^* is obtained by replacing in the optimal strategy under full information

$$h_t^{\text{full}} = (\sigma\sigma^\top)^{-1} \mu(Y_t)$$

the unknown drift $\mu(Y_t)$ by its filter $\widehat{\mu(Y_t)}$

Solution for Power Utility

Risk-sensitive control problem

Nagai & Runggaldier (2008), Davis & Lleo (2011)

Let $\quad Z^h := \exp\left\{\theta \int_0^T h_s^\top \sigma dB_s - \frac{\theta^2}{2} \int_0^T h_s^\top \sigma\sigma^\top h_s ds\right\}$

Change of measure: $\quad P^{(h)}(A) = E[Z^{(h)} 1_A] \quad$ for $\quad A \in \mathcal{F}_T$

Reward function

$$E_{t,x,p}[U(X_T^{(h)})] \quad = \quad \frac{x^\theta}{\theta} \underbrace{E_{t,p}^{(h)}\left[\exp\left\{-\int_t^T b(p_s, h_s) ds\right\}\right]}_{=:\ v(t,p,h)\ \text{independent of } x}$$

$$\text{where} \quad b(p,h) \quad := \quad -\theta\left(h^\top Mp - \frac{1-\theta}{2} h^\top \sigma\sigma^\top h\right)$$

Value function $\quad V(t,p) = \sup_{h \in \mathcal{H}} v(t,p,h) \quad$ for $0 < \theta < 1$

Find $h^* \in \mathcal{H}$ such that $\quad V(0,\pi) = v(0,\pi,h^*)$

HJB-Equation

State $\quad dp_t = \alpha(p_t, h_t)dt + \beta^\top(p_t)dB_t + \int_{\mathcal{Z}} \gamma(p_t, z)\widetilde{I}(dt \times dz)$

Generator $\quad \mathcal{L}^h g(p) = \frac{1}{2} tr\left[\beta^\top(p)\beta(p)D^2 g\right] + \alpha^\top(p,h)\nabla g$
$$+\lambda \int_{\mathcal{Z}} \{g(p+\gamma(p,z)) - g(p)\}\bar{f}(p,z)dz$$

$$V_t(t,p) + \sup_{h \in \mathbb{R}^n} \left\{ \mathcal{L}^h V(t,p) - b(p,h)V(t,p) \right\} = 0$$

terminal condition $\quad V(T,p) = 1$

Candidate for the Optimal Strategy

$$h^* = h^*(t,p) = \underbrace{\frac{1}{(1-\theta)}}(\sigma\sigma^\top)^{-1}\left\{ Mp + \frac{1}{V(t,p)}\sigma\beta(p)\,\nabla_p V(t,p) \right\}$$

myopic strategy $+$ correction

Certainty equivalence principle does not hold

Justification of HJB-Equation

- Standard verification arguments fail, since we cannot guarantee **uniform ellipticity** of the diffusion part: $tr\left[\beta^\top(p)\beta(p)D^2 V\right]$

$$\xi^\top\beta^\top(p)\beta(p)\xi \geq c|\xi|^2 \quad \text{for some } c > 0 \text{ and all } \xi \in \mathbb{R}^d$$

  satisfiable only if number of assets $n \geq$ number of drift states d

- Applying results and techniques from Pham (1998)

  $\Longrightarrow$ V is a unique continuous viscosity solution of the HJB-equation

Regularization of HJB-Equation

- Add a 'small' Gaussian perturbation $\frac{1}{\sqrt{m}} d\widetilde{B}_t$ to the SDE for the first $d-1$ components of the filter
- Consider control problem for the modified dynamics of the filter
- Modified HJB-equation has an additional diffusion term $\frac{1}{2m}\Delta V^m(t,p)$

  $\Longrightarrow$ uniform ellipticity
- Applying results from Davis & Lleo (2011)

  $\Longrightarrow$ classical solution $V^m(t,p)$ to the modified HJB-equation

  Standard verification results can be applied
- Convergence results for $m \to \infty$:

  optimal strategy to the modified control problem is an
  ε-optimal strategy to the original control problem

Approximation of the optimal strategy

→ Policy Improvement

→ Numerical solution of HJB equation

- Feynman-Kac formula for linearized HJB equation

Policy Improvement

Starting approximation is the myopic strategy $h_t^{(0)} = \frac{1}{1-\theta}(\sigma\sigma^\top)^{-1} M p_t$

The corresponding reward function is

$$V^{(0)}(t,p) := v(t,p,h^{(0)}) = E_{t,p}\Big[\exp\Big(-\int_t^T b(p_s^{(h^{(0)})}, h_s^{(0)})ds\Big)\Big]$$

Consider the following optimization problem

$$\max_h \left\{\mathcal{L}^h V^{(0)}(t,p) - b(p,h) V^{(0)}(t,p)\right\}$$

with the maximizer

$$h^{(1)}(t,p) = h^{(0)}(t,p) + \frac{1}{(1-\theta)V^{(0)}(t,p)}(\sigma^\top)^{-1}\beta(p)\nabla_p V^{(0)}(t,p)$$

For the corresponding reward function $V^{(1)}(t,p) := v(t,p,h^{(1)})$ it holds

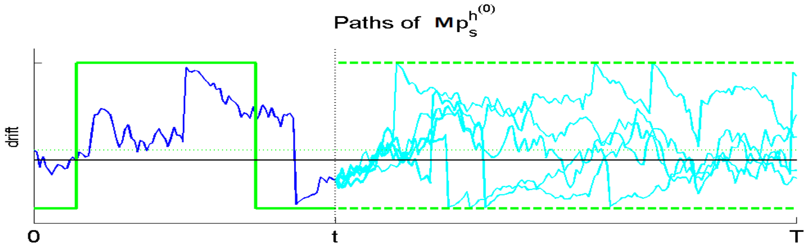
Lemma ($h^{(1)}$ is an improvement of $h^{(0)}$)

$$V^{(1)}(t,p) \geq V^{(0)}(t,p)$$

Policy Improvement (cont.)

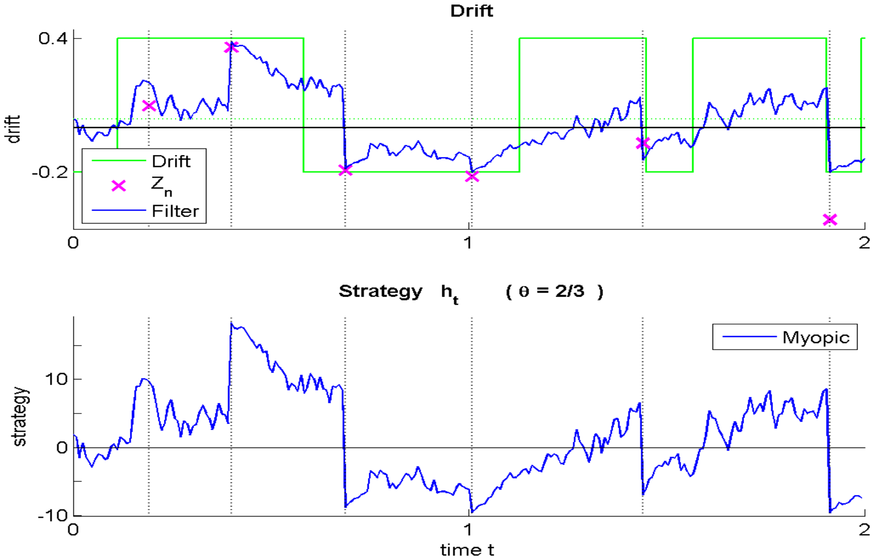
Policy improvement requires Monte-Carlo approximation of reward function

$$V^{(0)}(t,p) = E_{t,p}\Big[\exp\Big(-\int_t^T b(p_s^{(h^{(0)})}, h_s^{(0)})ds\Big)\Big].$$



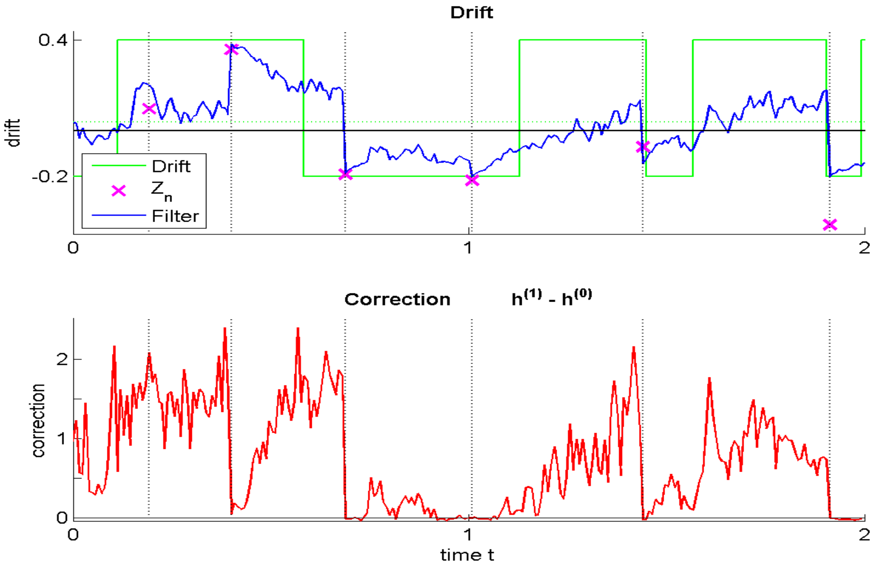
- Generate N paths of $p_s^{h^{(0)}}$ starting at time t with $p = p_t$
- Estimate expectation $E_{t,p}[\cdot]$
- Approximate partial derivatives $V^{(0)}_{p^k}(t,p)$ by finite differences
- Compute first iterate $h^{(1)}$

Numerical Results



Drift

Numerical Results



For $t = T_n$: nearly full information $\Longrightarrow$ correction ≈ 0

Numerical solution of HJB equation

HJB Equation

$$V_t(t,p) + \sup_{h\in\mathbb{R}^n} \left\{ \mathcal{L}^h V(t,p) - b(p,h)V(t,p) \right\} = 0$$

$$\text{terminal condition} \quad V(T,p) = 1$$

$$\text{Generator} \quad \mathcal{L}^h g(p) = \frac{1}{2} tr\left[\beta^\top(p)\beta(p) D^2 g\right] + \alpha^\top(p,h)\nabla g + \lambda \int_{\mathcal{Z}} \{g(p+\gamma(p,z)) - g(p)\} \bar{f}(p,z)dz$$

Plugging in the optimal strategy

$$h^* = h^*(t,p) = \underbrace{\frac{1}{(1-\theta)}(\sigma\sigma^\top)^{-1}\left\{ Mp \right.}_{\text{myopic strategy}} + \left. \frac{1}{V(t,p)}\sigma\beta(p)\nabla_p V(t,p) \right\}$$

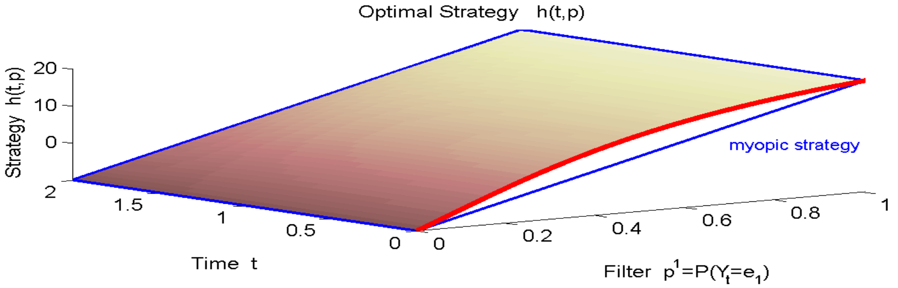
myopic strategy $+$ correction

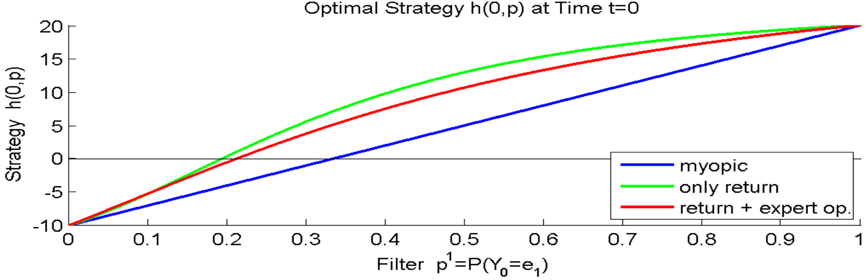
yields a nonlinear partial integro-differential equation

Normalization of $p \implies$ reduction to $d-1$ "spatial" variables

$d = 2$: only one "spatial" variable, ellipticity condition is satisfied

Numerical solution of HJB equation (cont.)





Conclusion

- Portfolio optimization under partial information on the drift
- Investor observes stock prices and expert opinions
- Non-linear HJB-equation with a jump part
- Computation of the optimal strategy

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