

Detecting bearish and bullish markets in financial time series using hierarchical hidden Markov models

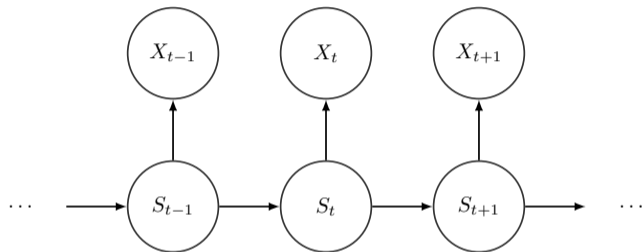
Lennart Oelschläger

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In a nutshell: Bearish and bullish markets



In a nutshell: The hidden Markov model



- $(X_t)_t$ – observed state-dependent process, $X_t | S_t = i \sim f_i$
- $(S_t)_t$ – state process, e.g. state space = {bullish, bearish, correction}

What we are going to talk about?

Why hierarchical hidden Markov models for financial time series data?

How to estimate such models?

How to decode the hidden states?

Model results for the DAX

Model results for the Goldman Sachs Group stock

How to perform model checking?

What's next?

Why hierarchical hidden Markov models for financial time series data?

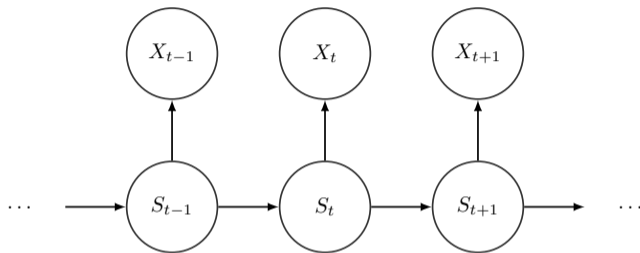
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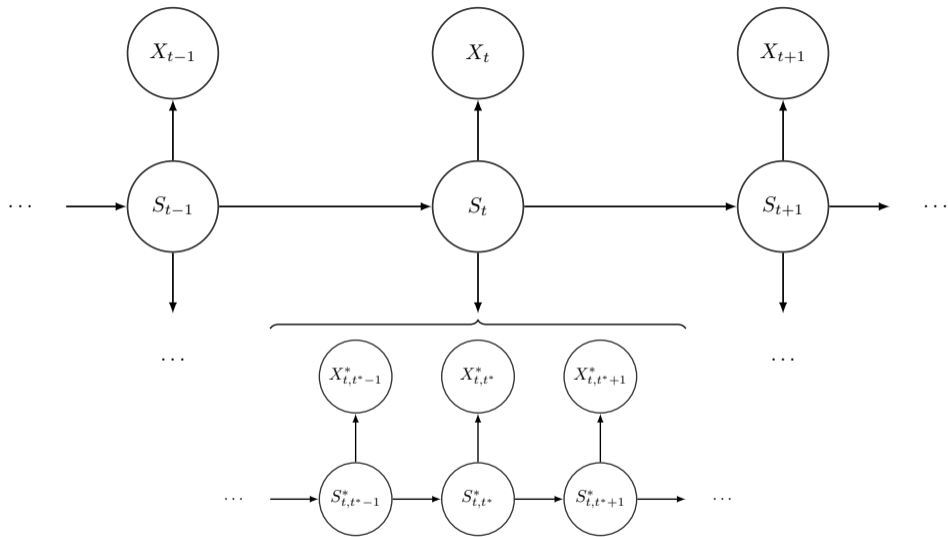
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How to perform model checking?



- 👍 successful results, leading to trading strategies that outperform e.g. buy-and-hold
- 👎 model does not capture short and long term trends jointly



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Likelihood of the i -th fine-scale hidden Markov model with the model parameters $\theta^{*(i)} = (\delta^{*(i)}, \Gamma^{*(i)}, (f^{*(i,k)})_k)$ on the t -th chunk $(X_{t,t^*})_{t^*}$ of fine-scale observations

$$\mathcal{L}^{HMM}(\theta^{*(i)} | (X_{t,t^*})_{t^*}) = \sum_{S_{t,1}^*, \dots, S_{t,T^*}^* = 1}^{N^*} \left(\prod_{t^*=1}^{T^*} f^{*(i, S_{t,t^*}^*)}(X_{t,t^*}) \right) \left(\delta_{S_{t,1}^*}^{*(i)} \prod_{t^*=2}^{T^*} \gamma_{S_{t,t^*-1}^* S_{t,t^*}^*}^{*(i)} \right)$$

Complexity: exponential

Maximum likelihood estimation

fine-scale forward probabilities

$$\alpha_{k,t^*}^{*(i)} = f^{*(i)}(X_{t,1}^*, \dots, X_{t,t^*}^*, S_{t,t^*}^* = k),$$

$$\mathcal{L}^{HMM}(\theta^{*(i)} \mid (X_{t,t^*}^*)_{t^*}) = \sum_{k=1}^{N^*} \alpha_{k,T^*}^{*(i)}.$$

$$\alpha_{k,1}^{*(i)} = \delta_k^{*(i)} f^{*(i,k)}(X_{t,1}^*),$$

$$\alpha_{k,t^*}^{*(i)} = f^{*(i,k)}(X_{t,t^*}^*) \sum_{j=1}^{N^*} \gamma_{jk}^{*(i)} \alpha_{j,t^*-1}^{*(i)}, \quad t^* = 2, \dots, T^*.$$

Complexity: linear

- parameter constraints \rightarrow bijective transformation
- numerical underflow \rightarrow logarithm
- local maxima \rightarrow repeated numerical search

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Viterbi algorithm

We are interested in

$$\arg \max_{S_1, \dots, S_T} f(S_1, \dots, S_T \mid X_1, \dots, X_T) = \arg \max_{S_1, \dots, S_T} f(S_1, \dots, S_T, X_1, \dots, X_T),$$

which we derive from

$$\xi_{i,t} = \max_{S_1, \dots, S_{t-1}} f(S_1, \dots, S_{t-1}, S_t = i, X_1, \dots, X_t),$$

which can in turn be calculated recursively via

$$\begin{aligned}\xi_{i,1} &= \delta_i f^{(i)}(X_1), \\ \xi_{i,t} &= \max_j (\xi_{j,t-1} \gamma_{ji}) f^{(i)}(X_t).\end{aligned}$$

Then

$$\begin{aligned}\hat{S}_T &= \arg \max_i \xi_{i,T}, \\ \hat{S}_t &= \arg \max_i \xi_{i,t} \gamma_{i \hat{S}_{t+1}}.\end{aligned}$$

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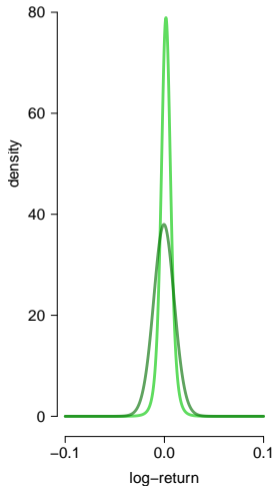
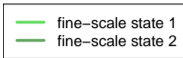
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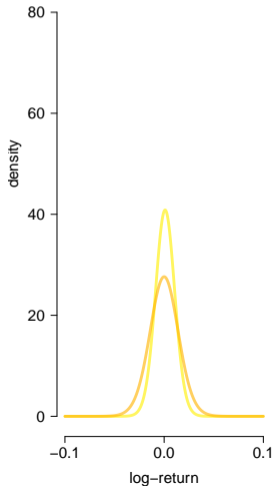
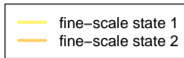
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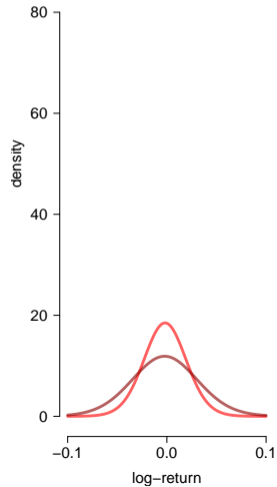
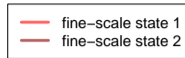
coarse-scale state 1

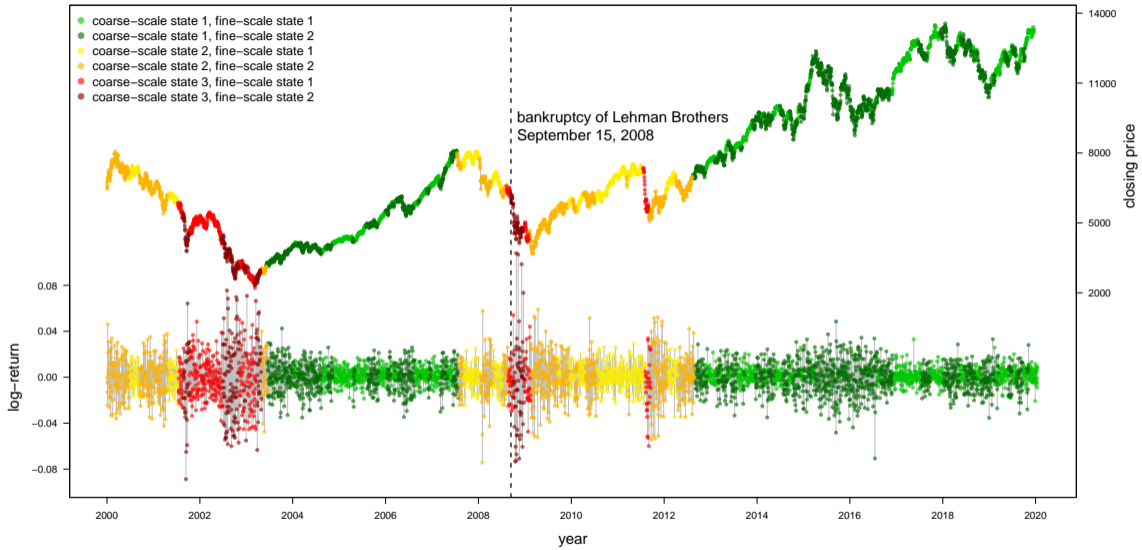


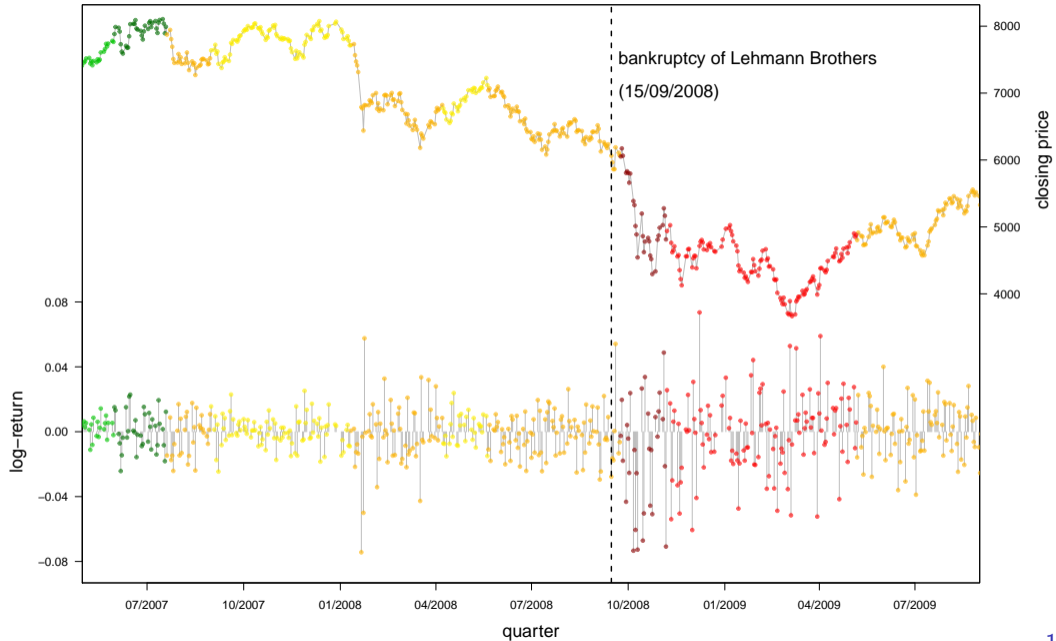
coarse-scale state 2



coarse-scale state 3







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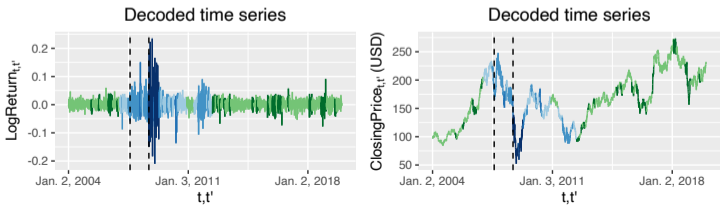
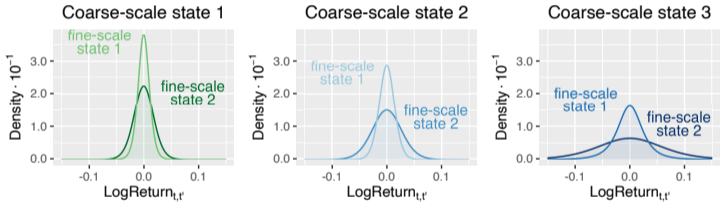
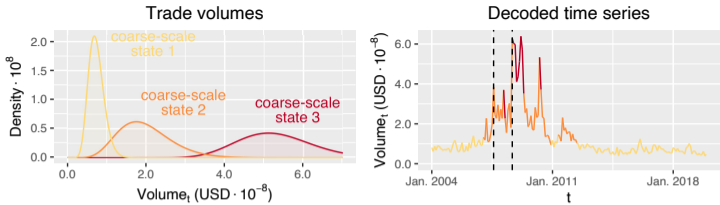
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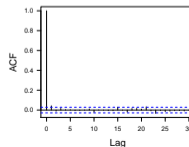
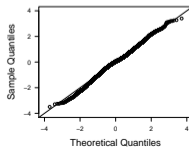
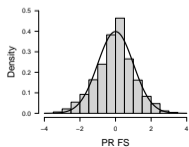
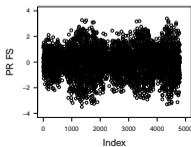
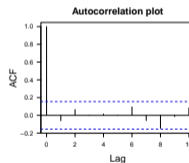
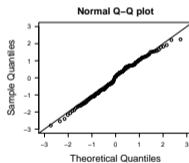
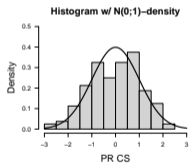
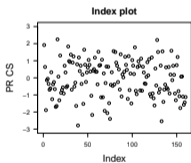
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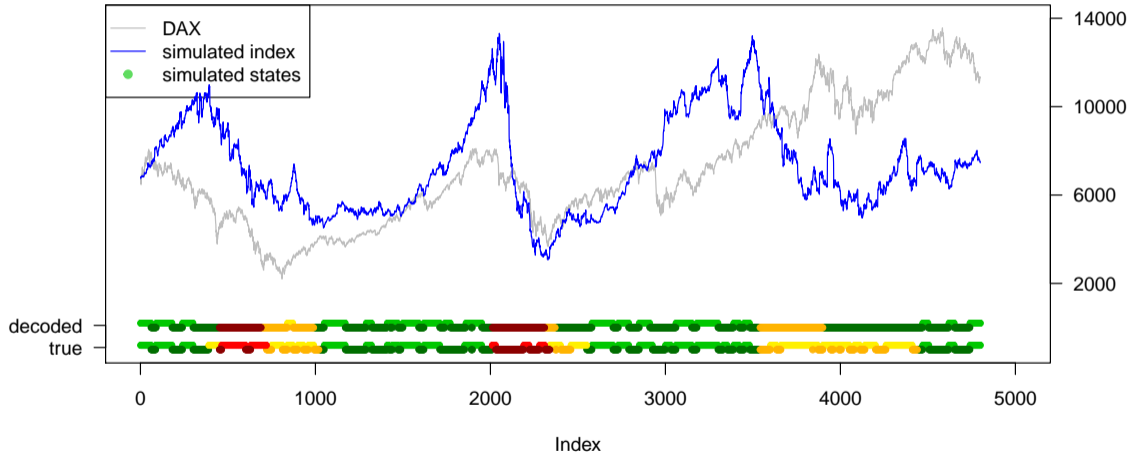
X_t has (invertible) distribution function $F_{X_t} \Rightarrow Z_t = \Phi^{-1}(F_{X_t}(X_t)) \sim \mathcal{N}(0, 1)$

Check:

- $Z_t \stackrel{a}{\sim} \mathcal{N}(0, 1)?$
- $\text{Cov}(Z_t, Z_{t+h}) \approx 0?$



Bootstrapping





«Think long-term. Prices rise or fall over months and years. There is no need to let yourself be driven crazy by short-term fluctuations.»

Thanks for your attention!