Time series modeling and forecasting based on a Markov chain with changing transition matrices

Summary

Main ideas

Subject: prediction in a financial time series based on a model in the form of Markov chains

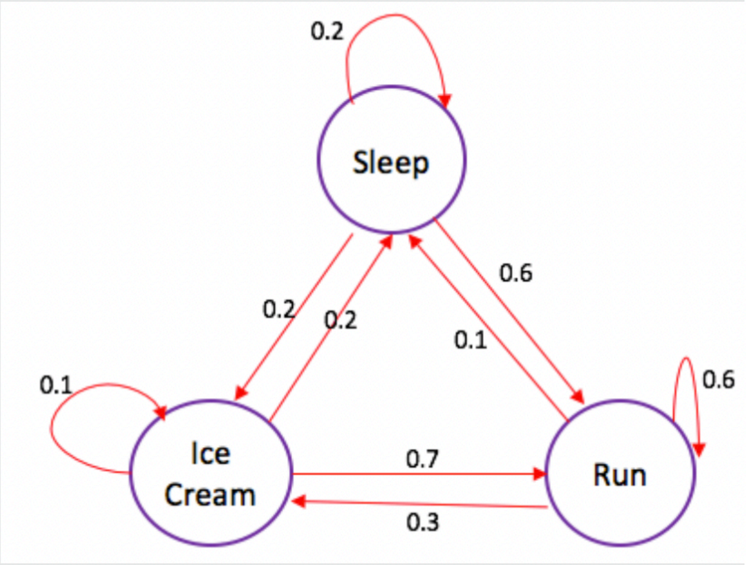
Optimization aim: finding the best window length, the number of windows and the number of intervals is to increase the predictive efficiency of the transition matrices

State: we should cluster time series in some uniformly distributed states and then predict the next state by Markov Chain

Trading: we should open long position for asset when the probability of the higher state is more, according to the Markov predictions, than the lower state. Vice versa – if this probability is less, we should open the short position

How do Markov Chains work

- We have some states and want to predict next state according to current state
- Principle: probability of the next state depends ONLY on the current state
- We should form transition matrices like that



NEXT STATE

CURRENT STATE

	SLEEP	RUN	ICE CREAM
SLEEP	0.2	0.6	0.2
RUN	0.1	0.6	0.3
ICE CREAM	0.2	0.7	0.1

Objects and graphs

- The main task is to determine number of windows, states and candles and then predict next states and realize trading strategy
- Let the process be in the state *Si lq(t),* then in the state *Sk lq(t + 1)* . We are interested in the probability of achieving "neighbor- ing" states *Si-1 l q(t + 1)* and *Si+1 l q(t + 1).*

N_b - the number of process states resulting from division of the range of changes observed between Y_{max} and Y_{min};
N_c – the number of candles (periods - 1 h or 1d, respectively, for each dataset) in the time window;
N_w - the number of time windows considered when calculating the transit matrix.

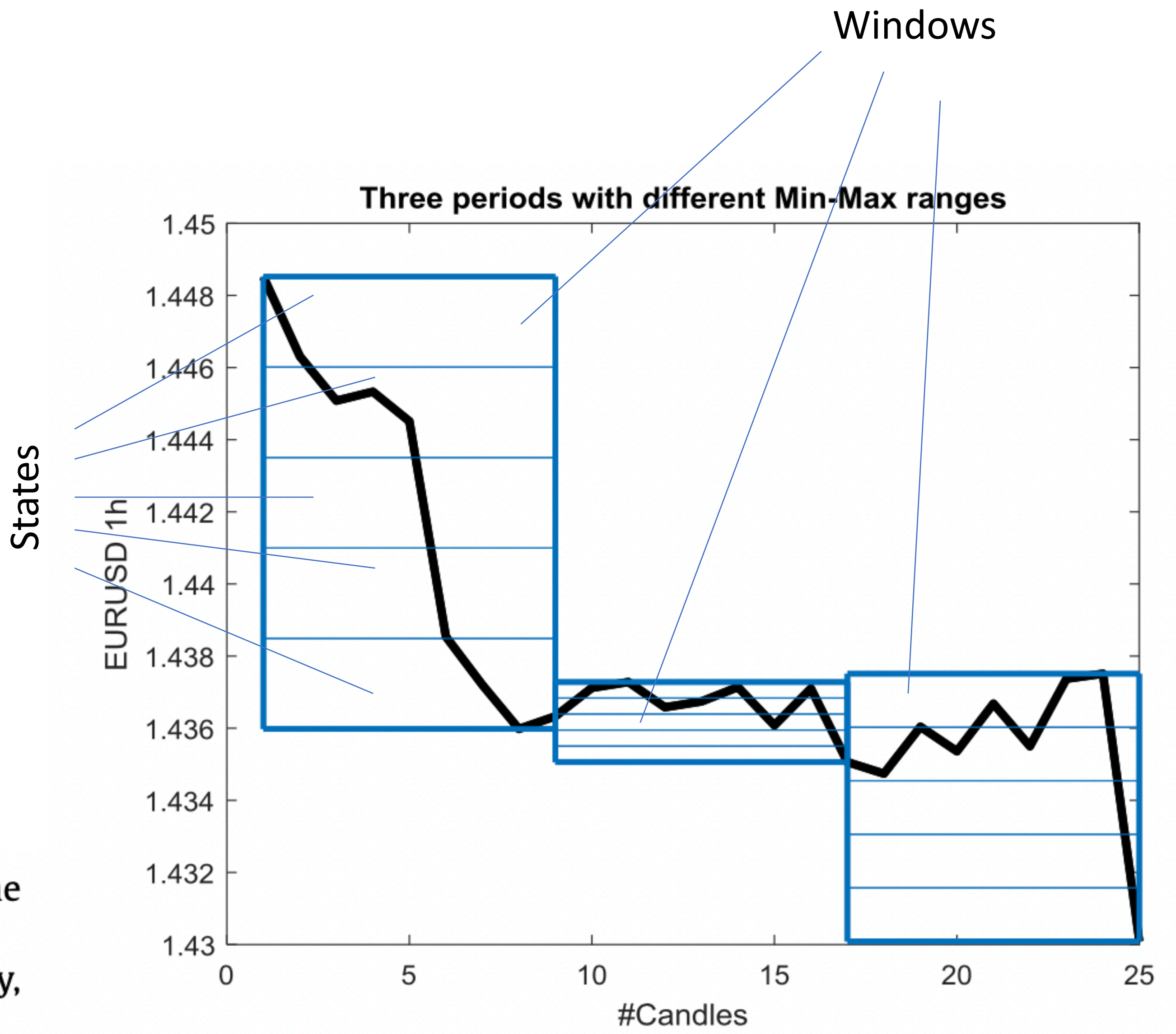


Fig. 3. Example of three adjacent 8-candle windows with varied ranges of max-min variation.

Trading strategy

–If $P_{i,i-1} < P_{i,i+1}$ open long positions;
–If $P_{i,i-1} > P_{i,i+1}$ open short positions

The risk was studied through the Calmar Ratio. This is the ratio of the final profit Z (J) to the maximum drawdown during the simulation - MDD:
$CR = Z(J)/MDD$; Simultaneous consideration of both factors requires a bicriteria approach, which is proposed here by using appropriate weights:
$C = w_c \cdot CR_{learn} + w_p \cdot Z(j)/J_{learn}$, $Z(J)/J_{learn}$ is a cumulative profit per candle at the end of the learning period

We alsp shoud make stop losses
$Z(j)=C_{j+1} - C_j$, (21) but if $L_j - C_j < -SL$,then
$Z(j) = -SL$;
where L_j – Low value in j-th candle;

Results

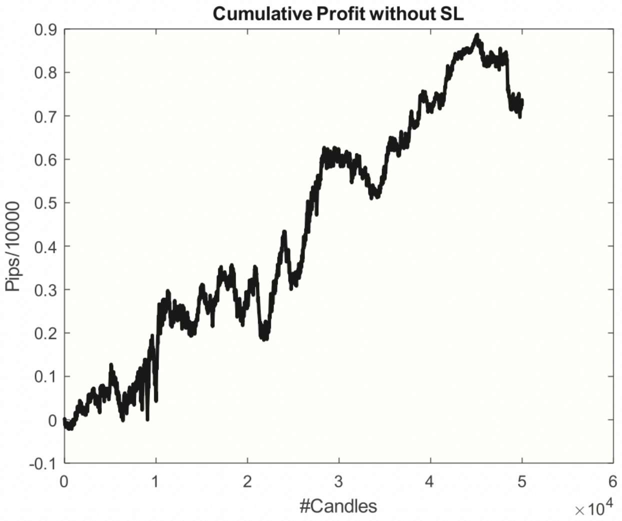


Fig. 4. Markov model cumulative profit curve without the interference of a brokerage platform i.e. without transaction costs and SL.

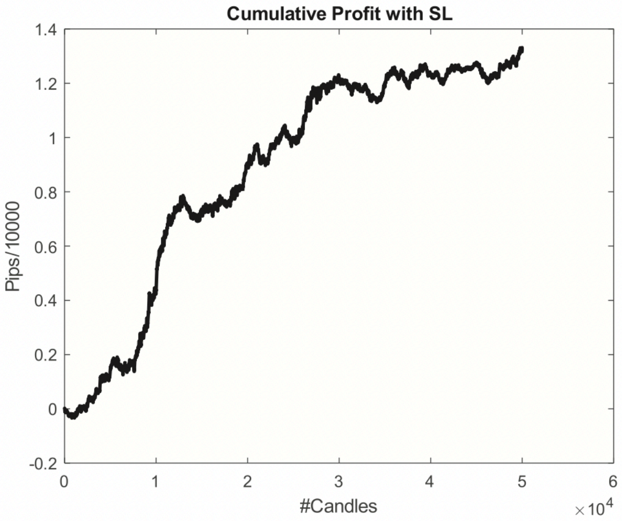


Fig. 5. A cumulative profit graph for a strategy tailored for implementation on a brokerage platform. Spread = 0.7 pips, SL = 10 pips.

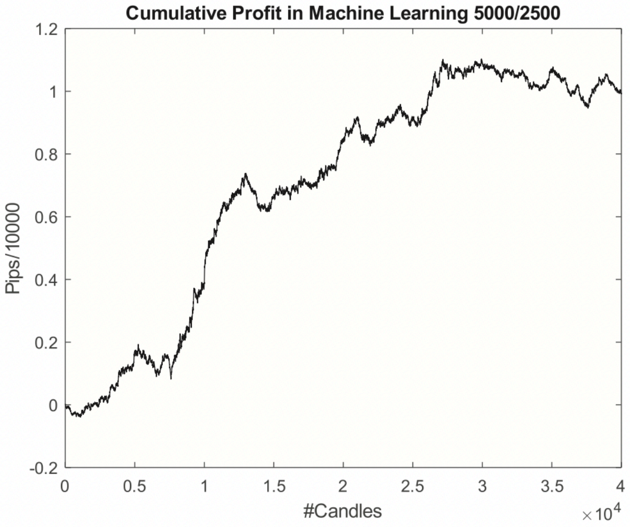


Fig. 10. Graph of the cumulative profit achieved in the machine learning mode. Test periods of 2500 candles were preceded by searches for the optimal parameters over periods of 5000 candles ($Z_s = 9934$ pips, Calmar = 6.3196).

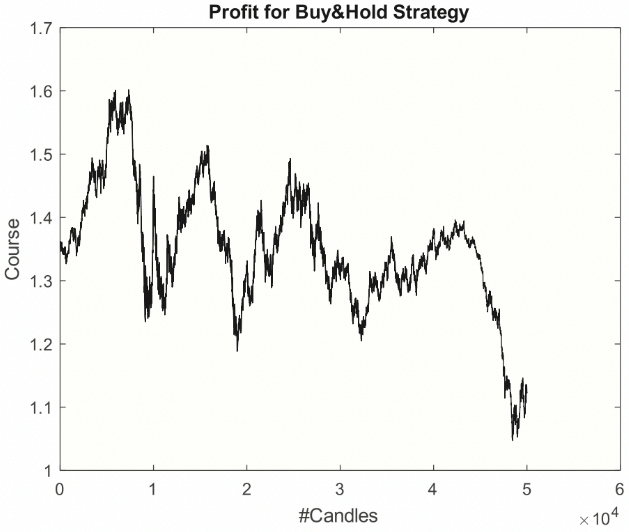


Fig. 12. Chart of the tested time series EUR/USD 1 h which determine the result of the Buy & Hold strategy.