An Introduction to Historically Consistent Neural Networks

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Motivation

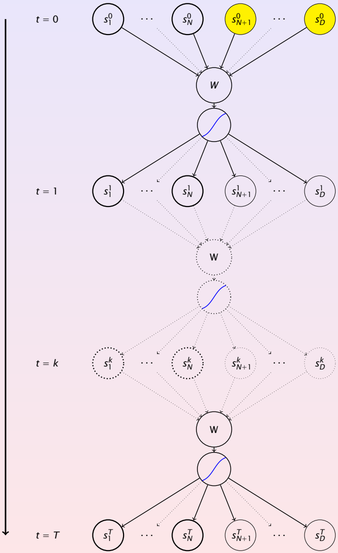
A financial time series modeler's wishlist. . .

- Model all relevant observables at once.
- Multi step forecasts.
- Acknowledge and quantify forecast uncertainty.
- Robustness with respect to the asset under consideration and with respect to selected data.
- Low model risk.

Outline

- Motivation
- Using Shared Layer Perceptrons (SLP) to build Historically Correct Neural Networks (HCNN)
- Applications
  - Value at Risk
  - Investment Decision Support
  - Optimal Control
- Conclusions and Outlook

Building Historically Correct Neural Networks



- Philosophy: acknowledge incomplete view of the world.
- Multi asset forecast.
- Multi step forecast.
- Uncertainty measure via ensemble.
- Memory enabled through hidden states.

Mathematical Formulation

State transition

$$\vec{s}^{\,t+1} = \tanh(W\vec{s}^{\,t})$$

Partial derivatives

$$\frac{\partial E}{\partial w_{i,j}} = \sum_{t=1}^{T} l_i^t \vec{s}_j^{\,t-1}$$

$$\vec{l}^{\,t} = (1 \ominus (\vec{s}^{\,t})^2) \otimes (W' \vec{l}^{\,t+1} \oplus \vec{\varepsilon}^{\,t})$$

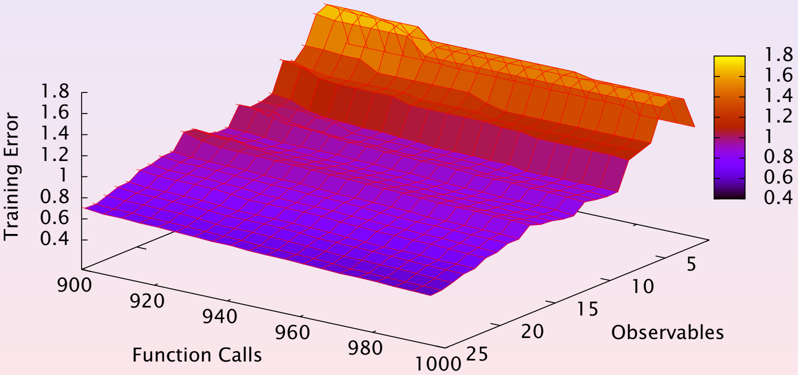
Training

- Teacher forcing
- Additive noise to increase robustness

Time Series

Name	Instrument	Region	Datastream
FTSE 100 Index	Equities	United Kingdom	FTSE100
DAX 30 Index	Equities	Germany	DAXINDX
CAC 40 Index	Equities	France	FRCAC40
FTSE MIB	Equities	Italy	FTSEMIB
Dow Jones Euro Stoxx 50	Equities	Europe	DJES50I
S&P 500 Index	Equities	United States	S&PCOMP
NASDAQ 100 Index	Equities	United States	NASA100
Nikkei 225 Index	Equities	Japan	JAPDOWA
Kospi Index	Equities	South Korea	KORCOMP
3 months LIBOR	Interest rate	United Kingdom	ECUK£3M
12 months LIBOR	Interest rate	United Kingdom	BBGBP12
Germany 3 months	Interest rate	Germany	ECWGM3M
France 3 months	Interest rate	France	ECFFR3M
Italy 3 months	Interest rate	Italy	ECITL3M
EURIBOR 3 months	Interest rate	Euro area	ECEUR3M
Eurodollars 3 months	Interest rate	United States (Europe)	ECUS$3M
Benchmark Bond 3 months	Interest rate	Japan	ECJAP3M
Benchmark Bond 10 years	Interest rate	United Kingdom	UKMBRYD
Bund Future 10 years	Interest rate	Germany	BDBRYLD
Benchmark Bond 10 years	Interest rate	France	FRBRYLD
Benchmark Bond 10 years	Interest rate	Italy	IBRYLD
US Treasuries 10 years	Interest rate	United States	USBD10Y
Benchmark Bond 10 years	Interest rate	Japan	JPBRYLD
US Dollar to Great British Pound	Exchange rate	United Kingdom	USDOLLR
US Dollar to Swiss Franc	Exchange rate	Switzerland	SWISFUS
US Dollar to Euro	Exchange rate	Euro area	USEURSP
Yen to US Dollar	Exchange rate	Japan	JAPAYE$
Gold Bullion	Commodity	United Kingdom (world)	GOLDBLN
Brent Crude Oil	Commodity	Europe (world)	OILBREN
CRB Index	Commodities	United States (world)	NYFECRB
Baltic Exchange Dry Index	Commodities	world	BALTICF

Improving Convergence



Value at Risk

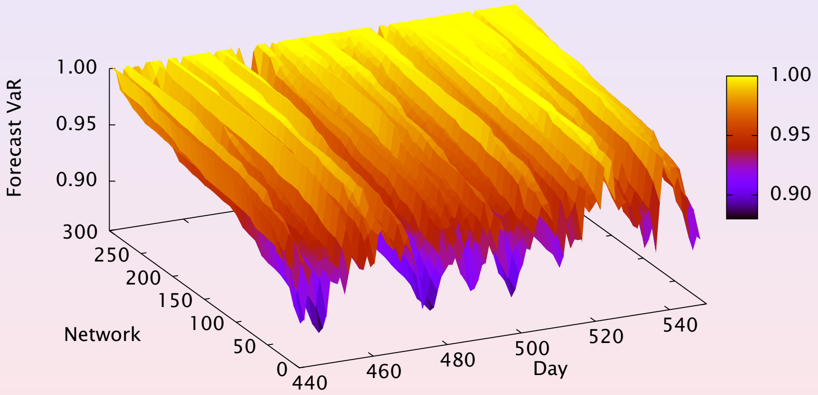
A good Value at Risk model should...

- give us an idea of the probable asset price over the next n days.
- produce only a limited number of violations.
- offer savings compared to, e.g., historical simulation.

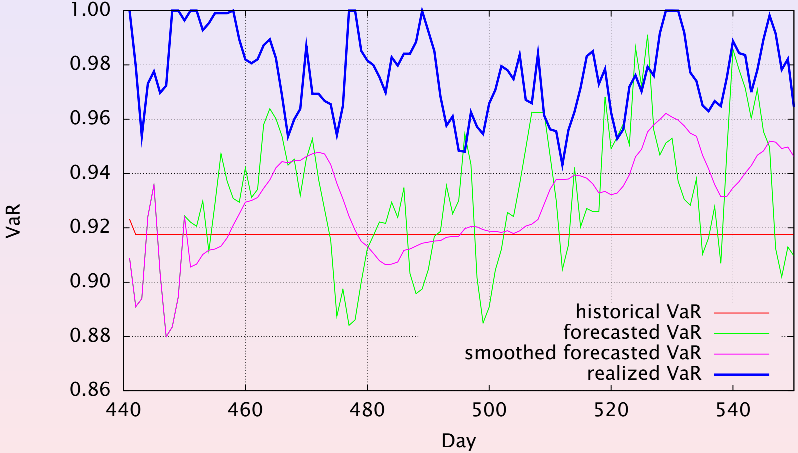
Idea

- Model Value at Risk using multi step forecasts over n days.
- Use an ensemble forecast to get a feeling for the probable distribution of returns.
- Try a multivariate model to enhance accuracy.

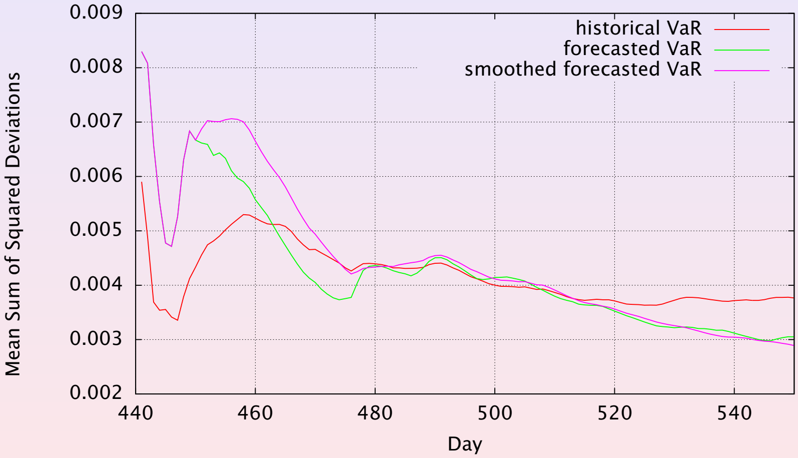
The Model: FTSE 100 Worst Portfolio Values



Results: FTSE 100 VaR Comparison



Results: FTSE 100 Deviations

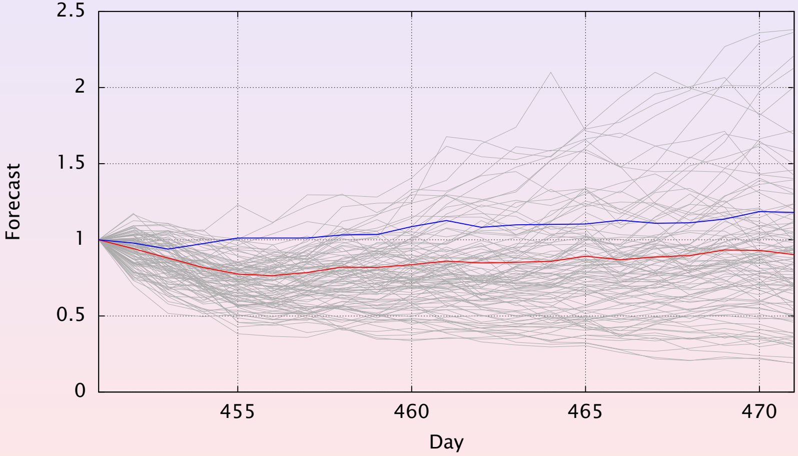


Results: Robustness with Different Assets

Asset	110d hist. vs. fc		8y hist. vs fc	
FTSE100	0.00376	0.00289	0.00817	0.00376
DAXINDX	0.00540	0.00430	0.01407	0.00546
FRCAC40	0.00354	0.00320	0.01102	0.00420
FTSEMIB	0.00405	0.00361	0.01222	0.00539
DJES50I	0.00329	0.00073	0.01127	0.00144
SPCOMP	0.00586	0.00473	0.00696	0.00512
NASA100	0.02919	0.02015	0.01198	0.03301
JAPDOWA	0.00613	0.00076	0.01002	0.00168
KORCOMP	0.01835	0.01513	0.01354	0.02648
USDOLLR	0.00107	0.00070	0.00134	0.00095
SWISFUS	0.00119	0.00024	0.00102	0.00038
USEURSP	0.00160	0.00142	0.00127	0.00240
JAPAYEUSD	0.00108	0.00093	0.00148	0.00199
GOLDBLN	0.00372	0.00163	0.00498	0.00155
OILBREN	0.03433	0.02145	0.02579	0.02892
NYFECRB	0.00145	0.00112	0.00306	0.00137
BALTICF	0.00399	0.00145	0.03715	0.00402

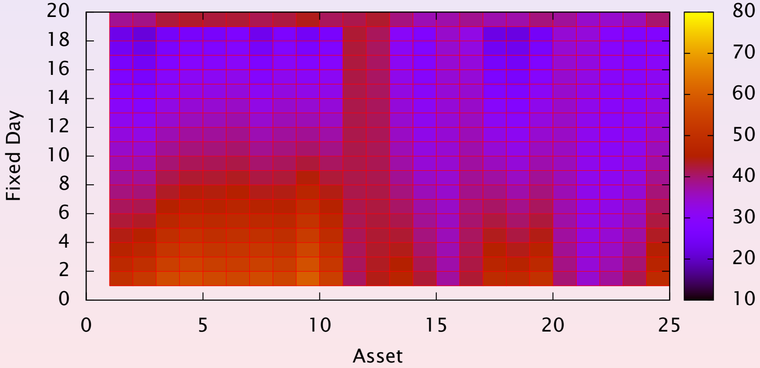
Market Timing: Gold

Gold price and forecast

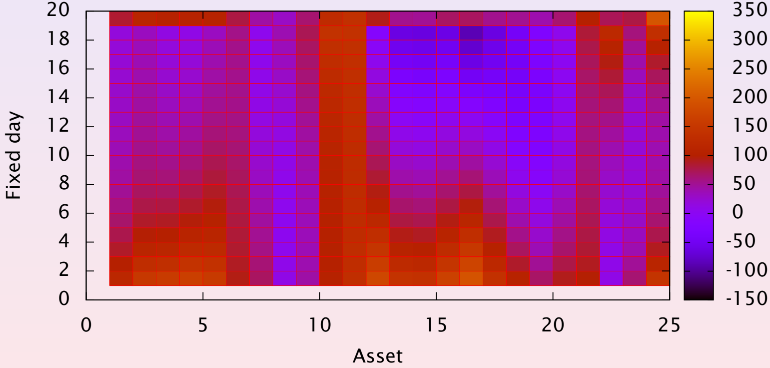


Short Term Results

Fixed day investment compared to neuro forecast



Fixed day investment compared to neuro forecast



Trading: Results for S&P500

type	r_a	r_a^{tc}	sharpe	maxDD	vol.	trades
naive	-0.085	-0.105	-0.45	-0.124	0.191	58
	-0.306	-0.693	-1.43	-0.946	0.214	1171
MA	0.051	0.047	0.26	-0.074	0.192	13
	-0.010	-0.080	-0.05	-0.619	0.220	213
NN	0.405	0.388	2.12	-0.076	0.191	50
	0.004	-0.325	0.02	-0.478	0.220	995
NNthr	0.146	0.133	1.11	-0.046	0.131	42
	-0.008	-0.293	-0.05	-0.444	0.184	863
NNdbl	0.239	0.228	1.70	-0.057	0.140	32
	0.005	-0.171	0.03	-0.303	0.159	535

First line: 110 days model runtime; second line: 8 years model runtime
r_a^{tc}: return after 0.033 percent transaction costs per roundtrip

Trading: Results for EUR|USD

type	r_a	r_a^{tc}	sharpe	maxDD	vol.	trades
naive	-0.019	-0.036	-0.18	-0.071	0.105	52
	0.002	-0.362	0.02	-0.253	0.099	1102
MA	-0.051	-0.056	-0.48	-0.093	0.106	16
	0.026	-0.050	0.26	-0.212	0.100	229
NN	0.168	0.155	1.60	-0.033	0.105	39
	-0.011	-0.307	-0.11	-0.375	0.100	898
NNthr	0.080	0.071	1.32	-0.021	0.061	29
	-0.028	-0.225	-0.41	-0.346	0.067	598
NNdbl	0.207	0.199	2.42	-0.023	0.085	25
	0.001	-0.172	0.02	-0.243	0.077	524

First line: 110 days model runtime; second line: 8 years model runtime
r_a^{tc}: return after 0.033 percent transaction costs per roundtrip

Comparing HCNN VaR with Copulae

Method	Exceedances 95%	Exceedances 99%	Mean Exceedances 95%	Mean Exceedances 99%	MSD 95%	MSD 99%
HS	95	25	0.7528	0.8249	2.5429	5.8189
ANN	**49**	**14**	**0.7079**	**0.7532**	**4.2343**	**8.9155**
GARCH-N-GCop	57	25	0.6837	0.6717	3.6900	6.2678
GARCH-N-tCop	58	24	0.6813	0.6589	3.6616	6.4620
GARCH-N-ClCop	30	12	0.7599	0.6862	5.2035	9.1594
GARCH-t-GCop	37	9	0.7623	0.7947	4.5739	9.7865
GARCH-t-tCop	38	9	0.7598	0.7572	4.5109	10.0588
GARCH-t-ClCop	20	2	0.7196	1.3598	6.8466	15.7424
APARCH-N-GCop	56	25	0.7041	0.6435	3.5826	6.0692
APARCH-N-tCop	57	23	0.6994	0.6554	3.5579	6.2590
APARCH-N-ClCop	31	10	0.7089	0.7512	5.0763	8.9086
APARCH-t-GCop	39	9	0.7051	0.7885	4.5503	9.6264
APARCH-t-tCop	39	9	0.7193	0.7361	4.4965	9.9057
APARCH-t-ClCop	22	2	0.6102	1.3904	6.8159	15.4624
FIGARCH-N-GCop	34	6	0.3824	0.2541	6.1955	11.4454
FIGARCH-N-tCop	36	5	0.3732	0.2593	6.0974	11.9871
FIGARCH-N-ClCop	26	4	0.3792	0.1362	7.0428	14.6084
FIGARCH-t-GCop	8	0	0.2096	0.0000	10.0834	30.2715
FIGARCH-t-tCop	9	0	0.2037	0.0000	10.1317	31.0134
FIGARCH-t-ClCop	8	0	0.2101	0.0000	11.5596	35.3465

MSD = Mean Squared Deviations

Conclusions and Outlook

- Historically Correct Neural Networks offer added value in financial time series applications.
- All computations are performed using a *single* model.
- We get a robust model working well over a range of assets and timespans, e.g., 8 years without retraining.
- The model generally beats its benchmarks.

- Can we extract more information from the distribution of returns?
- How far can we extend multi step forecasts?
- How can we determine relevant inputs?