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Censored Bernstein Quantile Networks for probabilistic precipitation forecasting

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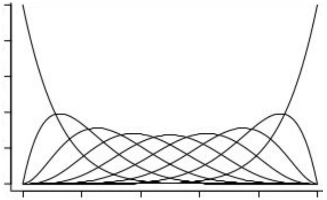
Bernstein Quantile Networks

… is a flexible method for distributional regression of continuous variables



- **Bernstein polynomial** as predictive quantile distribution
- **Neural network** to link distribution to input variables
- Estimation by minimising **quantile loss** averaged over predefined quantile levels

Bremnes (2020)

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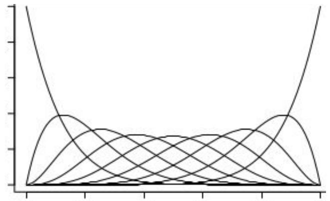

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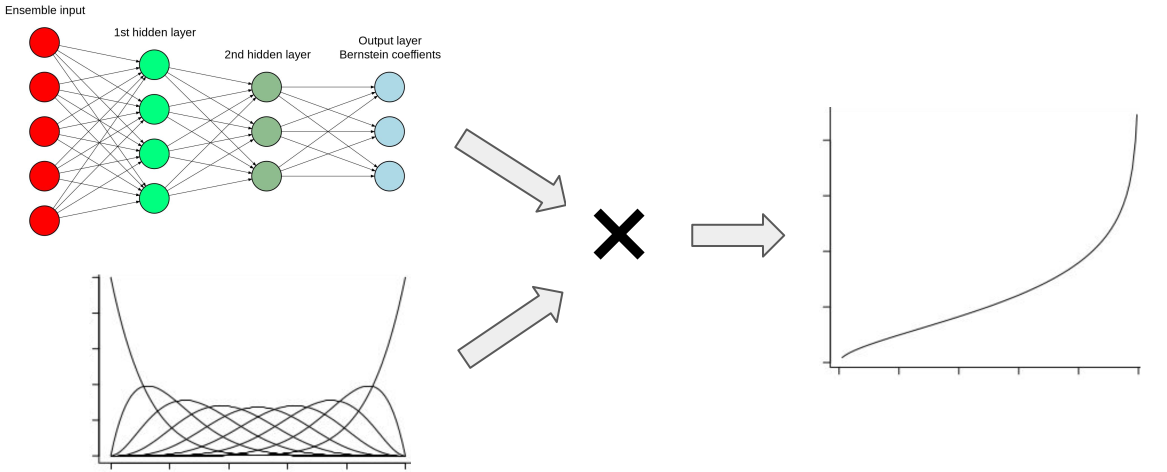

Bremnes (2020)

Statistical challenges with precipitation

Continuous variable with a (large) point mass at zero

- mixed distributed
- need special attention

Modelling options

- discretisation of precipitation $\rightarrow$ categorical modelling
- separate models for the zeros (discrete) and the positive amounts (continuous)
  - predictive distribution by combination of the two models
- continuous model where zeros are treated as censored values
  - introduce a latent variable with no lower bound
  - adjust loss function
  - truncate at zero (negative part = probability of no precipitation)

Censored Bernstein Quantile Networks

Alternative 1

- make a model for probability of precipitation **p(x)**
  - neural network, logistic regression, use of ensemble/scenarios, climatology etc.
- 1st epoch of BQN training
  - compute quantile loss only over levels τ and cases *x* where $\mathbf{p(x) > 1 - \tau, \forall \tau, x}$
- Remaining epochs
  - compute quantile loss for positive quantiles, i.e. over levels τ and cases *x* where $\mathbf{Q(\tau | x) > 0, \forall \tau, x}$

Censored linear single-quantile regression, Friederichs and Hense (2007)

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- Remaining epochs
  - compute quantile loss for positive quantiles, i.e. over levels τ and cases *x* where $\mathbf{Q(\tau|x) > 0,\ \forall \tau, x}$

Alternative 2

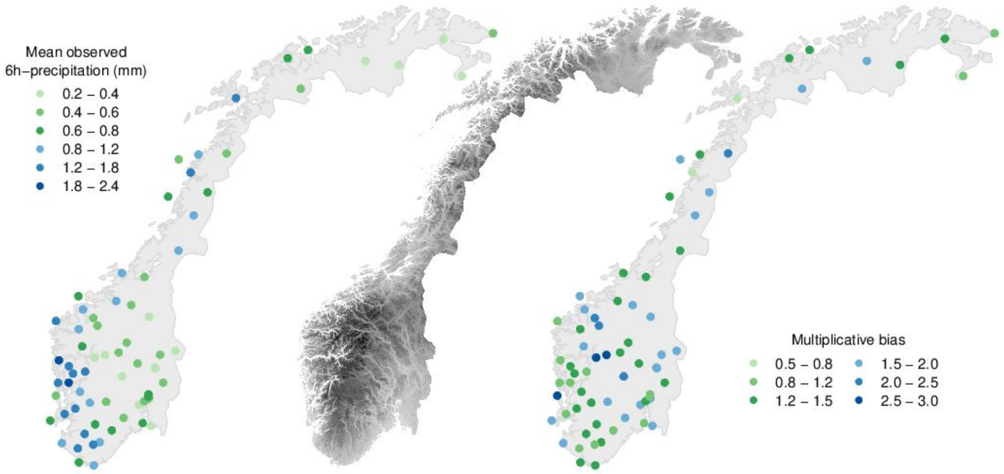
- all epochs
  - compute quantile loss for positive quantiles, i.e. over levels τ and cases *x* where $\mathbf{Q(\tau|x) > 0,\ \forall \tau, x}$
  - Note! random initialisation of network parameters implies random number of negative quantiles

Censored linear single-quantile regression, Friederichs and Hense (2007)

Example: 6h-precipitation forecasting

Data

- 70 Norwegian stations
- 00+66h ECMWF ENS reforecasts (11 members)
    - ensemble means of total precipitation, convective precipitation, total column cloud liquid water, CAPE, wind at 700 hPa
    - standard deviation of total precipitation
    - probability of precipitation
- training (#22997), validation (#5758) and test (#5633) datasets



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Methods (variants of BQN)

- no censoring
- censoring with probability input (alternative 1) from
  - neural network
  - logistic regression
  - ensemble
  - climatology
- censoring without probability input (alternative 2)
- 2-model approach
  - Neural net for probability of precipitation
  - BQN for positive precipitation amounts

Model selection/tuning and testing framework

- extensive tuning of each method on validation dataset
  - 4320 configurations trained and evaluated
- 5 best configurations of each method re-trained 5 times
  - predictions on test dataset (#5×5×5633)

Results

BQN method	Quantile Skill Score (%) Overall	Quantile Skill Score (%) Extremes*
No censoring	-0.35	0.16
Censoring: Neural net	0.79	1.38
Censoring: Logistic reg.	0.53	0.33
Censoring: Ensemble prb	0.53	0.69
Censoring: Climate	0.45	0.35
Censoring	0.15	-0.32

2-model approach applied as reference

*) Extremes = 3 most extreme ENS cases for each station, 3×70 = 210 cases

Results

BQN method	Quantile Skill Score (%)		Brier Skill Score (%)			
	Overall	Extremes*	0 mm	0.05 mm	0.1 mm	10 mm
No censoring	-0.35	0.16	-215.80	-5.24	-3.54	-0.14
Censoring: Neural net	0.79	1.38	-2.24	-2.51	-2.65	0.79
Censoring: Logistic reg.	0.53	0.33	-1.86	-2.04	-2.13	0.13
Censoring: Ensemble prb	0.53	0.69	-1.38	-1.44	-1.50	0.03
Censoring: Climate	0.45	0.35	-1.89	-2.00	-2.04	0.44
Censoring	0.15	-0.32	-3.48	-3.83	-3.98	0.14

2-model approach applied as reference

*) Extremes = 3 most extreme ENS cases for each station, 3×70 = 210 cases

Conclusions

Extending BQN to precipitation forecasting by means of censoring works very well

- at least as good as the 2-step modelling approach wrt quantile score
- using a probability of precipitation as input has a slightly positive impact
  - less important how it is derived

Non-censored BQN works satisfactorily

- except for very small/traces of precipitation amounts
  - adhoc truncation of very small precipitation amounts may help though