Probabilistic Short-Term Low-Voltage Load Forecasting using Bernstein-Polynomial Normalizing Flows

Climate Change AI ICML 2021 Workshop

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June 26, 2021

Probabilistic Short-Term Low-Voltage Load Forecasting

- Energy sector is the major contributor to greenhouse gas emissions [6]
- Utilization of renewable energy can be increased by short-term load forecast [3]
- Especially at the low level the distributions are complex and multimodal
- Probabilistic forecasts estimate the distribution to quantify uncertainty for more informed decision-making [4]

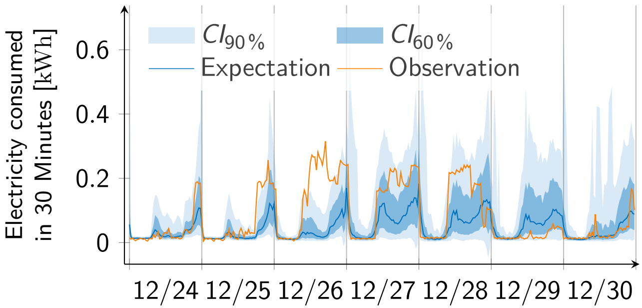
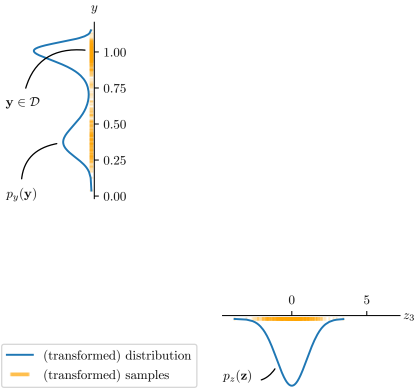


Figure: Exemplary load forecast in Christmas week based on data from [1].

Bernstein-Polynomial Normalizing Flows (BNF)



In a Nutshell

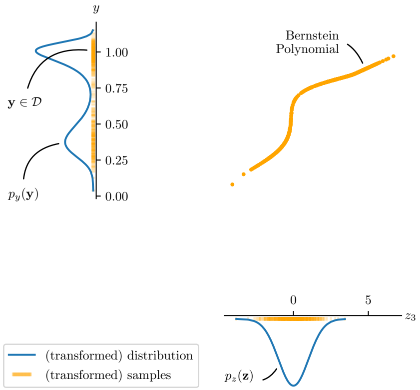
Normalizing Flows fit a parametric bijective function f that transforms between a complex target distribution $p_y(y)$ and a simple distribution $p_z(z)$, often $p_z(z) = N(0,1)$.

Change of Variable Formula

Evaluate the probability $p_y(y)$ from the simple probability $p_z(z)$ as follows:

$$p_y(\mathbf{y}) = p_z(f(\mathbf{y})) \left|\det \nabla f(\mathbf{y})\right|^{-1} \tag{1}$$

Bernstein-Polynomial Normalizing Flows (BNF)

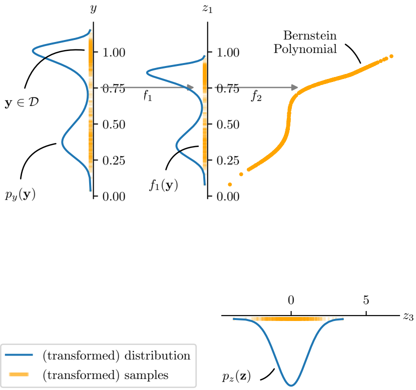


- Bernstein polynomials h^M of order M, approximate any function on $y \in [0, 1]$ [2].
- M controls the flexibility at no cost to the training stability [5].

$$h^M(y) = \frac{1}{M+1} \sum_{i=0}^{M} \mathrm{Be}_i^M(y) \vartheta_i(\mathbf{x})$$

With covariates $\mathbf{x}$ such as lagged power consumption at earlier time steps, holiday indicator and calendar variables.

Bernstein-Polynomial Normalizing Flows (BNF)

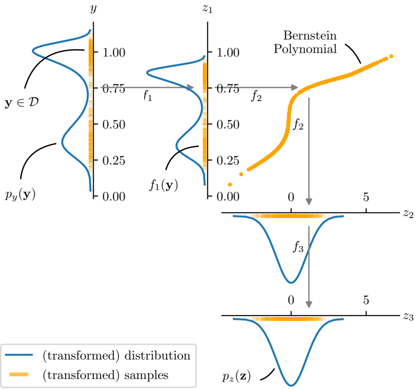


$$f_1 : z_1 = a_1(\mathbf{x}) \cdot y - b_1(\mathbf{x})$$

$$f_2 : z_2 = \frac{1}{M+1} \sum_{i=0}^{M} \mathrm{Be}_i^M(z_1)\vartheta_i(\mathbf{x})$$

With covariates $\mathbf{x}$ such as lagged power consumption at earlier time steps, holiday indicator and calendar variables.

Bernstein-Polynomial Normalizing Flows (BNF)



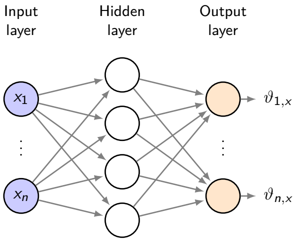
$$f_1 : z_1 = a_1(\mathbf{x}) \cdot y - b_1(\mathbf{x})$$

$$f_2 : z_2 = \frac{1}{M+1} \sum_{i=0}^{M} \mathrm{Be}_i^M(z_1)\vartheta_i(\mathbf{x})$$

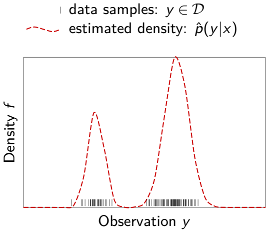
$$f_3 : z_3 = a_2(\mathbf{x}) \cdot y$$

With covariates $\mathbf{x}$ such as lagged power consumption at earlier time steps, holiday indicator and calendar variables.

Maximum Likelihood Estimation



Neural Network:
$n(\mathbf{x}, \omega) = \theta_x$ with $\mathbf{x} = [x_1, \ldots, x_n]^T \in \mathcal{D}$



Conditioned probability density:
$\hat{p}(y, \theta_x)$ with $\theta_x = [\vartheta_{1,x}, \ldots, \vartheta_{n,x}]^T \in \Theta$

Choose the parameters of the model so that the observed data has the *highest likelihood*.

$$\mathcal{L}(\mathcal{D}|\omega) = \prod_{i=0}^{m} \hat{p}(y_i, n(\mathbf{x}_i, \omega))$$

$$\hat{\omega} = \arg\max_{\omega \in \Omega} \{\mathcal{L}(\mathcal{D}|\omega)\}$$

Maximum likelihood estimation

Results of empiric experiments

Architecture	Model	CRPS	NLL	MAE	MSE
FC	BNF (ours)	0.021	-123.157	0.414	9.430
FC	GMM	0.026	-114.892	0.360	0.464
FC	GM	1.314	-75.101	1.027	53.203
FC	QR	0.026	-	0.415	4.351
1DCNN	BNF (ours)	0.017	-132.089	0.342	0.429
1DCNN	GMM	0.019	-125.933	0.384	0.450
1DCNN	GM	0.018	-101.290	0.347	0.366
1DCNN	QR	0.017	-	0.321	0.399

Abbreviations

FC Fully connected neural network
1DCNN dilated 1D-Convocational neural network
BNF Bernstein-Polynomial Normalizing Flow
GM Gaussian model
GMM Gaussian mixture model
QR Quantile regression

CRPS Continuous ranked probability score
NLL Negative logarithmic likelihood
MAS Mean absolute Error
MSE Mean Squared Error

Summary

- BNFs are a powerful and stable method to express complex distributions, with almost no regularization or special tuning.
- This makes them a preferential choice over quantile regression or mixture models for probabilistic load forecasts.
- BNFs allow sampling form the learned distribution to generate synthetic load data for research or scenarios used for grid planning.

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Thanks for your interest, especially also on behalf of my colleagues:

- Marcus Voss
- Beate Sick
- Mark Nigge-Uricher
- Oliver Dürr

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