Applications of variational inference in the Bank of Russia

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APPLICATIONS OF VARIATIONAL INFERENCE
IN THE BANK OF RUSSIA

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Bayesian estimation of macro models

Vector Autoregressions

Dynamic Factor Models

Dynamic Stochastic General Equilibrium Models

Agent Based Models
Bayesian techniques for intractable posterior

Sampling (asymptotically sample from exact posterior)

- Gibbs Sampling (Casella and Goerge (1992));
- Importance Sampling (Owen (2013));
- Metropolis-Hastings (Chib and Greenberg (1995));
- Hamiltonian Monte Carlo (Neal (2011));
- No-U-Turn Sampling (Hoffman and Gelman (2014));
- Sequential Monte Carlo (Doucet, De Freitas and Gordon (2001));
- PDMP Continuous-Time Monte Carlo (Fearnhead et al. (2016)).

Optimization (allows to estimate larger models)

- MAP estimation;
- Expectation Propagation algorithm (Minka (2001));
- Variational Bayes estimation (Wainwright and Jordan (2008));
- $\alpha$-divergence (Li and Turner (2016)).
What does VB offer?

**Approximate posterior**
- Chooses the posterior approximation from a family of distributions that allows independent sampling.

**Solving via optimization**
- Finds an approximate posterior minimizing KL divergence between posterior and approximation family;
- Allows achieving the same accuracy faster than MCMC methods;
- Allows estimating posterior simultaneously maximizing the marginal likelihood with respect to hyperparameters.

**Large-scale applications**
- Estimates models with thousands/dozens of thousands of parameters on Desktop PC.
Variational Bayes

A VB algorithm maximizes the lower bound of the logarithm of the marginal likelihood with respect to an approximate density and hyperparameters:

\[
\log p(y|x, \varphi) = \log \int p(y, \theta|x, \varphi)d\theta = \log \int \frac{p(y|\theta, x, \varphi)p(\theta|\varphi)}{q(\theta)} q(\theta)d\theta \geq \\
\int (\log p(y, \theta|x, \varphi) - \log q(\theta)) q(\theta)d\theta = \\
\log p(y|x, \varphi) - \int (\log q(\theta) - \log p(\theta|y, x, \varphi)) q(\theta)d\theta = \\
\log p(y|x, \varphi) - KL(q(\theta)||p(\theta|y, x, \varphi)) = ELBO(q, \varphi)
\]
Different approximate densities might be useful in different situations

Mean-field approximations (Independent Gaussian approximation)
• All components are independent distributions (Wainwright and Jordan (2008)).

Gaussian approximation
• Gaussian distribution (Tan, Bhaskaran and Nott (2019)).

Neural network (Normalizing flows)
• Simple distribution is passed through a neural network (Rezende and Mohamed (2015)).

Non-parametric approximation (Stein variational inference)
• Approximate functional space optimization (Liu and Wang (2019)).
Sparse Bayesian neural network for inflation forecasting

Neural network

- Highly non-linear and flexible model;
- Sparse Bayesian regularization (Tipping (2001)) to avoid overfitting and minimize cross-validation dimensionality.

Model performance

- Bayesian neural network is usually comparable with or better than other ML models for inflation prediction;
- Due to a sparse structure, it can be easy to find the most important features (Khabibullin and Seleznev (2020)).

*Mean-field variational approximation is used.*
Seasonal adjustment model for financial flows

Financial flow data
• A financial flow report which helps monitor real-time industry inflows and outflows was created at the start of the COVID-19 crisis;
• Existence of daily, weakly and monthly seasonality greatly complicates the understanding of reasons behind changes in indicator dynamics.

Seasonal adjustment
• Hundreds of series are smoothed every day;
• Models without flexible trends (RW trend with SV) show poor performance for some series.

*Mean-field and normalizing flows variational approximation is used. For uncertainty estimation, Stein VI produces significantly more accurate results.

Daily seasonal adjustment during the COVID-19 crisis using models with and without a flexible trend proposed by Khabibullin et al. (2020)
Incorporating economic judgment into nonlinear models

Guided non-structural model

• An extension of the idea suggested by Del Negro and Schorfheide (2004);
• Real data and artificial data from a structural model are used for the estimation of a non-structural model;
• The final algorithm for the joint structural and non-structural (hyper)parameters estimation is a double variational inference or ADVIL (Li et al. (2019)).

Results

• Economic judgment from the DSGE model helps to improve BNN model results.

*Mean-field and normalizing flows variational approximations are used.
Conclusion

• Variational inference helps in the estimation of models that cannot be estimated via classical Bayesian techniques;
• Our experience shows that even poor mean-field approximation is usually sufficient for practical applications.