# Bayesian Ensembling: Unified Framework for Bayesian Model Selection

Fedor Sobolevskiy, Mukhamadsharif Nabiev, Dmitriy Vasilenko, Vadim Kasyuk

**Abstract**

We develop a unified library for Bayesian model selection and ensembling, integrating multiple Bayesian inference methods under a single interface. The library provides modular components for model ensembling through posterior sampling, making Bayesian methods accessible for deep learning tasks.

## 1 Motivation

Bayesian methods provide principled uncertainty estimation but suffer from fragmented implementations across multiple libraries. Our project unifies these approaches into a single framework focused on model ensembling, where each algorithm defines strategies to sample models from posterior distributions.

## 2 Planned Algorithms

### 2.1 Core Methods

- **Practical Variational Inference (ELBO)**: With local reparameterization trick and pruning heuristic
- **Scalable Laplace Approximation**: Kronecker-factored Hessian for efficient posterior approximation
- **Variational Rényi Bound**: Generalization of ELBO using Rényi divergence for flexible inference
- **Probabilistic Backpropagation**: Moment propagation with Gaussian posterior approximations

### 2.2 Baseline Comparisons

- Hamiltonian Monte Carlo (HMC)
- Monte Carlo Dropout

# 3 Library Design

- **Unified API**: Single interface for all Bayesian ensembling methods
- **Model Agnostic**: Works with MLP architectures
- **Posterior Sampling**: Each algorithm provides different sampling strategies
- **Hyperparameter Tuning**: Built-in optimization for method-specific parameters

# 4 Planned Figures

## 4.1 Headline Figure: Unified Bayesian Ensembling Framework

**Description:** A conceptual diagram showing the unified architecture:

- **Input Layer**: MLP model architectures
- **Inference Layer**: Parallel Bayesian methods (ELBO, Laplace, Rényi, HMC, MC Dropout) generating posterior samples
- **Aggregation Layer**: Weighted combination of samples based on posterior probabilities
- **Output Layer**: Final ensemble predictions with uncertainty quantification

## 4.2 Figure 2: Method Comparison Scatter Plot

**Description:** Performance comparison of all implemented methods:

- **X-axis**: Prediction Performance (task-specific metric)
- **Y-axis**: Expected Calibration Error (ECE)
- **Point colors**: Different Bayesian methods
- **Point size**: Training time or computational cost
- **Highlight**: Optimal Pareto front showing best performance-calibration trade-offs

## 4.3 Figure 3: Library Architecture Diagram

**Description:** Technical architecture of the unified library:

- **Core API Layer**: Unified interface for users
- **Method Abstraction Layer**: Common interface for all Bayesian algorithms
- **Implementation Layer**: Specific implementations of each method
- **Evaluation Module**: Standardized metrics and benchmarking tools

# 5 Experimental Plan

- **Datasets**: UCI benchmarks and synthetic datasets
- **Models**: MLP architectures of varying complexity
- **Metrics**: Performance metrics, calibration error, computational efficiency
- **Implementation**: Building on existing PyTorch implementations