TreeFlow: Going Beyond Tree-based Parametric Probabilistic Regression

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ML in PL Conference 2023

26 - 29 October / Warsaw, Poland



Deterministic vs. Probabilistic Regression

Use Case

Future State Prediction Car entering a roundabout

Deterministic Regression

There is exactly only one position.

Probabilistic Regression

There is a distribution of possible positions.





The Quintessence of TreeFlow

Probabilistic Regression for Tabular Data with a Flexible Distribution



Univariate Multimodal Distributions





Multivariate Multimodal Distributions

Fact #1

Tree-based ensembles excel in classification and regression with mixed-type variable tabular data.









LightGBM

Fact #2

Current approaches use Gaussian or parametric distributions for uncertainty modeling, e.g., NGBoost, CatBoost, PGBM.



Fact #3

Existing methods struggle to handle **multi-modal distributions** and do not support high-dimensional probabilistic predictions.



Here comes the TreeFlow!

TreeFlow: Main Characteristics

Regression model for tabular data Numerical and categorical data **Univariate** and **multivariate** targets Non-Gaussian, non-parametric distributions Probabilistic and deterministic predictions

TreeFlow: Architecture



Tree-based Feature Extractor - extract the vector of binary features from the structure of the tree-based ensemble model. **Shallow Feature Extractor** - a shallow neural network; maps high-dimensional binary vectors to low-dimensional feature space. **Conditional Continuous Normalizing Flow** - takes previous vector as a conditioning factor; models complex probability distribution.



A Word About Normalizing Flows



TreeFlow: Training



TreeFlow: Sampling







Why flexibility of the distribution is important?







Toy Example



P(Y|X)P(Y|X)P(Y|X)

P(Y|X)

$$egin{aligned} X_1 &= 0, X_2 = 0) = \mathcal{N}(Y|\mu = 0, \sigma = 1) \ X_1 &= 0, X_2 = 1) = \mathcal{E}(Y|\lambda = rac{1}{3}) \ X_1 &= 1, X_2 = 0) = rac{1}{2}\mathcal{N}(Y|\mu = -10, \sigma = 1) \ &+ rac{1}{2}\mathcal{N}(Y|\mu = 10, \sigma = 1) \ X_1 &= 1, X_2 = 1) = \Gamma(Y|k = 7.5, heta = 1.0) \end{aligned}$$

Univariate Flexible Probabilistic Regression





Multivariate Flexible Probabilistic Regression



DATASET	Ind NGBoost	NGBOOST	r
Parkinsons scm20d WindTurbine Energy usFlight	6.86 94.40 -0.65 166.90 9.56	5.85 94.81 -0.67 175.80 8.57	
Oceanographic	7.74 ± 0.02	$7.73{\pm}0.02$	

Summary

- First-time usage of tree-based models to flexibly model probabilistic regression.
- A novel approach for combining tree-based models with conditional normalizing flows.
- SOTA results for both probabilistic (NLL, CRPS) and deterministic (RMSE) on a variety of datasets.

Thank you for your attent on!

Questions?









