The Proper Care and Feeding of CAMELS: How Limited Training Data Affects Streamflow Prediction

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Abstract

Accurate streamflow prediction largely relies on historical records of both meteorological data and streamflow measurements. For many regions around the world, however, such data are only scarcely or not at all available. To select an appropriate model for a region with a given amount of historical data, it is therefore indispensable to know a model’s sensitivity to limited training data, both in terms of geographic diversity and different spans of time. In this study, we provide decision support for tree- and LSTM-based models. We feed the models meteorological measurements from the CAMELS dataset, and individually restrict the training period length and the number of basins used in training. Our findings show that tree-based models provide more accurate predictions on small datasets, while LSTMs are superior given sufficient training data. This is perhaps not surprising, as neural networks are known to be data-hungry; however, we are able to characterize each model’s strengths under different conditions, including the “breakeven point” when LSTMs begin to overtake tree-based models.

1 Introduction

Accurate streamflow predictions are an indispensable prerequisite for water management and flood forecasting. There is a long history of research that employs machine-learning techniques to model streamflow, and a number of studies have shown that data-driven techniques can outperform traditional approaches based on physical models [2, 3, 6, 10]. Accurate predictions given scarce training data are especially important, as access to historical records of streamflow and meteorological measurements are exceedingly limited in many regions of the world. Even in the United States, the number of streamflow gauging stations is on the decline [4].

It is well-known that machine learning algorithms are data-hungry and produce more accurate models the more data they are fed. However, not all data-driven techniques exhibit the same degree of data demand: while neural networks generally need a lot of training data to yield accurate predictions, tree-based models have been shown to work well when provided with limited training data in certain domains. In light of this tension between a data-scarce problem and data-hungry algorithms, our study aims to provide guidance for two particular types of data-driven models, tree- and Long Short-Term Memory (LSTM) cell-based architectures. We answer the question, “where is the breakeven point?” or, in other words: How much training data do we need before LSTMs outperform tree-based models? In our experiments, we use the CAMELS dataset as we believe that it is sufficiently large and diverse to support some degree of generalization and application to other scenarios.

While LSTMs are clearly a suitable choice for the problem at hand, tree-based models might seem like a poor fit for this task. In recent years, however, researchers and practitioners have used gradient-boosted regression trees (GBRT) with great success in numerous time-series prediction

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tasks [7, 8, 9, 11]. Related to streamflow prediction, Gauch et al. [5] found XGBoost, a framework for GBRT, to provide more accurate predictions than LSTMs. In a similar study, Kratzert et al. [10] successfully applied LSTM-based architectures to predict streamflow. The two studies, however, worked with different datasets: While Gauch et al. used gridded forcing data for watersheds in the Lake Erie region, Kratzert et al. used the far larger CAMELS dataset [15], which includes basin-averaged forcings for watersheds across the continental United States. Hence, the results of both studies cannot be directly compared, and it remains unclear how the predictive quality of tree- and LSTM-based models compares on data spanning different regions and time spans.

To find out, we compare the prediction accuracy of XGBoost and LSTMs when trained on differently-sized subsets of the CAMELS dataset. We individually restrict the number of available training years and the number of basins to varying degrees. Our findings show that LSTMs outperform XGBoost if training data are abundant—which is as expected. When training data are limited, however, XGBoost provides more accurate predictions than LSTM-based architectures. Both types of models not only benefit from additional training years, but also from additional basins, which suggests that the models might be generalizing or transferring knowledge across basins. We consider this a promising result towards predictions on ungauged basins, where we aim to predict streamflow without access to any historical records for a given basin.

2 Data and Methods

We replicate the setup in Kratzert et al. [10] and train and test our models using the same meteorological forcings and streamflow measurements from the CAMELS dataset [15]. This dataset, curated by the US National Center for Atmospheric Research (NCAR), contains daily streamflow measurements for 671 basins across the continental United States. Following Newman et al. [14], we only use 531 basins and discard basins that exhibit large discrepancies in their areas as calculated using different strategies. Additionally, the dataset provides three sets of daily basin-averaged meteorological forcings for each basin. Again, we follow Kratzert et al. and use the Maurer forcings [12] that include cumulative precipitation, minimum and maximum air temperature, average short-wave radiation, and vapor pressure for each basin.

Building upon the open-source code of Kratzert et al., we are able to largely replicate their Entity-Aware LSTM (EA-LSTM) results with differences in median Nash–Sutcliffe-efficiency (NSE) well below 0.01, which can be easily attributed to non-determinism in the training process. We use the XGBoost framework to train gradient-boosted regression trees [1] and compare them to the EA-LSTM architecture proposed by Kratzert et al. For both model types, we use NSE as the objective or loss function. Appendix A provides details about the tuning and training procedures for both models, as well as our computational environment. Our code, data, and models are publicly available at https://github.com/gauchm/ealstm_regional_modeling.

All models obtain as input 27 static catchment attributes that provide properties of climate, vegetation, soil, and topography (cf. [10, Appendix A]) as well as the five normalized meteorological variables from the Maurer forcings [12]. As in Kratzert et al., the EA-LSTM model operates on the last 270 days of forcings. Due to limited computational resources, we focus on the EA-LSTM architecture and do not evaluate standard LSTMs. We feed the XGBoost model the last 30 days of forcings as a flattened vector of 30 times five variables, concatenated with the 27 catchment attributes. We only use a history of 30 days for XGBoost, as it has been our experience that, beyond a certain point, longer histories do not improve predictions. Likely, this is due to the fact that history length affects the input dimension by a multiplicative factor, as we use a flattened vector as input. A history of 270 days would therefore result in a $270 \times 5 + 27 = 1377$-dimensional input space, where training is far more challenging. Further, this would drastically increase the runtime of the computationally-intensive hyperparameter search. To reduce errors due to random initialization, we train each architecture with eight different seeds and evaluate the ensemble of their averaged predictions.

We evaluate the quality of each model by varying the amount of training data in two dimensions: the number of training years and the number of basins. All training periods start from October 1999 and last three, six, or nine years. The basins are random subsets of 2.5%, 5%, 10%, 50%, and 100% of the 531 basins. For the conditions that do not include all basins, we evaluate five different random basin selections each. Following exactly the same setup as Kratzert et al., we test all models on the
we apply Bonferroni correction and test our hypotheses at $\alpha = 0.05$ (after Bonferroni correction) and Cohen's $d = 0.01$.

Table 1: Minimum, mean, median, and maximum NSE scores and average number of failed basins (NSE $\leq 0$) on the test period for XGBoost and EA-LSTM models, trained with different amounts of data. The values are aggregated over five different random basin selections.

| Number of training years | Number of basins | Model           | Min  | Mean  | Median | Max   | Average number of failures |
|--------------------------|------------------|-----------------|------|-------|--------|------|---------------------------|
| 3                        | 13               | EA-LSTM        | −0.26| 0.15  | 0.16   | 0.54 | 1.6                       |
|                          |                  | XGBoost         | −0.43| 0.34  | 0.32   | 0.61 | 0.2                       |
|                          | 26               | EA-LSTM        | −0.09| 0.30  | 0.31   | 0.56 | 0.2                       |
|                          |                  | XGBoost         | −2.04| 0.36  | 0.40   | 0.73 | 0.6                       |
|                          | 53               | EA-LSTM        | −0.12| 0.46  | 0.48   | 0.81 | 0.2                       |
|                          |                  | XGBoost         | −1.65| 0.44  | 0.47   | 0.81 | 0.1                       |
|                          | 265              | EA-LSTM        | −0.23| 0.60  | 0.64   | 0.90 | 0.4                       |
|                          |                  | XGBoost         | −1.92| 0.51  | 0.55   | 0.84 | 4.8                       |
|                          | 531              | EA-LSTM        | 0.03 | 0.64  | 0.68   | 0.93 | 0.0                       |
|                          |                  | XGBoost         | −1.34| 0.53  | 0.57   | 0.87 | 8.0                       |
| 6                        | 13               | EA-LSTM        | −0.07| 0.42  | 0.44   | 0.68 | 0.2                       |
|                          |                  | XGBoost         | −0.37| 0.44  | 0.49   | 0.74 | 0.6                       |
|                          | 26               | EA-LSTM        | −0.05| 0.52  | 0.54   | 0.81 | 0.2                       |
|                          |                  | XGBoost         | −4.14| 0.46  | 0.53   | 0.78 | 0.8                       |
|                          | 53               | EA-LSTM        | 0.06 | 0.59  | 0.63   | 0.89 | 0.0                       |
|                          |                  | XGBoost         | −1.15| 0.55  | 0.58   | 0.86 | 0.4                       |
|                          | 265              | EA-LSTM        | −0.20| 0.67  | 0.71   | 0.94 | 1.2                       |
|                          |                  | XGBoost         | −3.08| 0.58  | 0.63   | 0.90 | 3.6                       |
|                          | 531              | EA-LSTM        | −1.42| 0.68  | 0.72   | 0.94 | 3.0                       |
|                          |                  | XGBoost         | −1.75| 0.60  | 0.64   | 0.91 | 5.0                       |
| 9                        | 13               | EA-LSTM        | 0.08 | 0.50  | 0.52   | 0.81 | 0.0                       |
|                          |                  | XGBoost         | −0.30| 0.48  | 0.51   | 0.78 | 0.4                       |
|                          | 26               | EA-LSTM        | −0.06| 0.57  | 0.60   | 0.89 | 0.2                       |
|                          |                  | XGBoost         | −2.41| 0.51  | 0.57   | 0.81 | 0.6                       |
|                          | 53               | EA-LSTM        | −0.03| 0.63  | 0.67   | 0.92 | 0.2                       |
|                          |                  | XGBoost         | −1.22| 0.58  | 0.61   | 0.89 | 0.6                       |
|                          | 265              | EA-LSTM        | −0.81| 0.69  | 0.73   | 0.96 | 0.8                       |
|                          |                  | XGBoost         | −4.91| 0.60  | 0.65   | 0.91 | 3.8                       |
|                          | 531              | EA-LSTM        | −1.10| 0.70  | 0.74   | 0.95 | 2.0                       |
|                          |                  | XGBoost         | −1.21| 0.62  | 0.66   | 0.91 | 6.0                       |

For each combination of training period and number of basins, we test the null hypothesis that the observed NSE values for EA-LSTM and XGBoost are drawn from the same distribution; for this, we use a Kolmogorov-Smirnov significance test. We further use a paired Wilcoxon significance test to compare the two models’ observed NSE values at the level of individual basins, assessing the null hypothesis of identical population mean ranks. To account for the large number of significance tests, we apply Bonferroni correction and test our hypotheses at $\alpha = 0.01/15$ [13]. Lastly, we estimate the corresponding effect size as Cohen’s $d$.

3 Results

Figure 1 and Table 1 provide an overview of our experimental results. Each plot in a particular row and column in Figure 1 corresponds to a combination of number of basins and training period length, and it shows the two models’ empirical cumulative NSE distributions. An ideal model with perfect predictions would exhibit a “J”-shaped distribution, yielding high NSE values for all basins. We specifically highlight cases in which the Kolmogorov-Smirnov significance test supports rejecting the null hypothesis of identical distributions at $p < 0.01/15$ (after Bonferroni correction) and Cohen’s
Figure 1: Empirical cumulative NSE distributions for XGBoost (green) and EA-LSTM (orange) at varying amounts of training data in terms of training period (columns) and number of basins (rows). Each plot shows the $p$-value of a Kolmogorov-Smirnov significance test and the effect size as Cohen’s $d$. Plots with gray backgrounds correspond to combinations with $p < 0.01/15$ and $d > 0.35$. 

\begin{align*}
&3 \text{ years, 13 basins} & p = 9.78 \times 10^{-7}, d = 1.01 \\
&6 \text{ years, 13 basins} & p = 1.95 \times 10^{-1}, d = 0.10 \\
&9 \text{ years, 13 basins} & p = 9.88 \times 10^{-1}, d = 0.11 \\
&3 \text{ years, 26 basins} & p = 8.27 \times 10^{-7}, d = 0.26 \\
&6 \text{ years, 26 basins} & p = 4.17 \times 10^{-1}, d = 0.17 \\
&9 \text{ years, 26 basins} & p = 2.50 \times 10^{-3}, d = 0.24 \\
&3 \text{ years, 53 basins} & p = 1.47 \times 10^{-1}, d = 0.10 \\
&6 \text{ years, 53 basins} & p = 7.22 \times 10^{-7}, d = 0.29 \\
&9 \text{ years, 53 basins} & p = 4.10 \times 10^{-3}, d = 0.33 \\
&3 \text{ years, 265 basins} & p = 2.24 \times 10^{-51}, d = 0.46 \\
&6 \text{ years, 265 basins} & p = 1.63 \times 10^{-55}, d = 0.42 \\
&9 \text{ years, 265 basins} & p = 3.03 \times 10^{-55}, d = 0.38 \\
&3 \text{ years, 531 basins} & p = 1.16 \times 10^{-32}, d = 0.58 \\
&6 \text{ years, 531 basins} & p = 7.28 \times 10^{-26}, d = 0.46 \\
&9 \text{ years, 531 basins} & p = 9.11 \times 10^{-23}, d = 0.45 
\end{align*}
As the heatmaps in Figures 4 and 5 show, the accuracy of XGBoost and EA-LSTMs on individual basins is strongly correlated, while XGBoost is slightly more accurate for most basins if trained on small training sets (Figure 4) and slightly less accurate for most basins if trained on large datasets (Figure 5). Furthermore, it appears that both models make poor predictions on the same basins, with a few exceptions where XGBoost yields much worse predictions than the EA-LSTM model. Based on manual examination of the results, the difference in these striking instances can be explained by only a few days in which XGBoost vastly overestimates the daily streamflow. As the NSE metric is highly sensitive to outliers, this decreases the affected basin’s overall score.

$d > 0.35$, which is halfway between the scales suggested by Sawilowsky for “small” and “medium” effect sizes [16]. Table 1 lists the models’ minimum, mean, median, and maximum NSE scores for each training set size, as well as the average number of “failures” (basins with NSE below zero) across the five different random basin selections.

As expected, less training data—both in terms of training period length and number of basins—reduces the prediction accuracy of all models; this is shown by the leftward shift of the distributions in Figure 1. In cases where both training period and number of basins are very limited (for instance, the cases of six years and 13 basins or three years and 26 basins or less), XGBoost outperforms the EA-LSTM architecture with an increasing effect size as dataset size decreases. There appears to be a breakeven point around 43,000 to 58,000 training samples (we define a sample as one day’s streamflow for one basin), which equates to about 2.4%–3.3% of the maximum training set size: XGBoost and EA-LSTMs exhibit similar NSE distributions at the combinations of three years and 53 basins ($3 \times 365 \times 53 \approx 58,000$), six years and 26 basins ($6 \times 365 \times 26 \approx 57,000$) as well as nine years and 13 basins ($9 \times 365 \times 13 \approx 43,000$). With access to more training data, EA-LSTMs begin to outperform XGBoost at small to medium effect sizes [16]. The effect size grows with the number of basins, but it has no clear relationship to the number of training years.

Comparing the extremes in Table 1, we further note that the EA-LSTM model results in higher minimum NSE values and fewer failed basins (NSE < 0) for all combinations except the most limited condition of three years and 13 basins. The EA-LSTM’s maximum NSE scores are also better than XGBoost’s whenever the mean and median are better. Notably, unlike mean, median, and maximum, both models’ minimum NSE values neither clearly improve with training period length nor with the number of basins. The same holds true for the average number of failed basins. This is especially surprising for the training period length, as the models obtain more samples for the same set of basins, which should improve their predictions. Likely, however, the added samples—most of which show modest streamflow—enticed the models to more conservative predictions near the bulk of the training samples, which results in worse NSE values when a more extreme event occurs.

Following the Kolmogorov-Smirnov significance test, we can reject the hypothesis of identical NSE distributions for the combination of three years and 13 to 26 basins, six to nine years/53 basins, and all combinations with at least 265 basins where $p < 0.01/15$. The paired Wilcoxon test provides similar conclusions and results in significant $p$-values less than 0.01/15 for the same combinations, in addition to nine years/13 basins, albeit the non-significant $p$-values are smaller than for the Kolmogorov-Smirnov test.

Figure 2 shows the correlation between the number of training samples and the median NSE scores for XGBoost (circles) and EA-LSTMs (squares), and it distinguishes training set size between training period length (marker size) and number of basins (marker color). Where circles are above squares of the same size and color, it means that XGBoost provides more accurate predictions than EA-LSTMs for that condition. We note that both models benefit not only from longer training periods, but also from larger basin subsets: Even if the number of training years remains constant but only the number of basins increases (lighter colors in Figure 2), the models’ predictions improve.

In a more aggregated view, Figure 3 plots the models’ median NSE distributions bucketed into different orders of magnitude in terms of training set size. Consistent with Figure 1, we see that EA-LSTMs overtake XGBoost between 40,000 and 80,000 training samples, and that more data generally result in better and more consistent prediction quality. There is a strong positive correlation between training set size and median NSE scores up to about 160,000 samples. For even larger training sets, the median NSE values mostly continue to grow, but we clearly see diminishing returns.
Figure 2: Correlation between number of training samples (logarithmic scale) and median NSE for XGBoost (circles) and EA-LSTM (squares). Marker size represents the training period length (three to nine years). Color encodes the number of basins (13–531). As we use five random basin subsets of each size, we report five median NSE scores for the combinations with less than 531 basins.

Figure 3: Distribution of median NSE values for XGBoost (green) and EA-LSTM (orange) bucketed into different orders of magnitude in terms of training set size. The boxplots aggregate each model’s results for combinations with similar amounts of training data.
Figure 4: Heatmap visualization of the XGBoost and EA-LSTM models’ NSE values for each basin. Both architectures are trained on three years and 13 basins (only shows basins that are part of at least one random 13-basin subset).

Figure 5: Heatmap visualization of the XGBoost and EA-LSTM models’ NSE values for each of the 531 basins. Both architectures are trained on nine years and all basins.
4 Discussion and Future Work

While our results show that—somewhat unsurprisingly—more training data generally improve predictions, our findings also paint a more nuanced picture: We note that not only longer training periods, but also data from additional basins increase model prediction accuracy. This is an important finding, as it suggests that the models actually infer relations between catchment characteristics and streamflow patterns, rather than merely overfitting on the given set of basins in the training data. While this effect is visible for both models, the growing effect size of the difference in NSE distributions indicates that EA-LSTMs benefit more than XGBoost from larger basin sets. The ability to generalize knowledge across basins is especially relevant for predictions in data-poor regions, as it implies that we might improve results in these areas by leveraging additional training data from similar basins in other, more data-rich regions.

In future work, it appears worthwhile to explore the potential of transfer learning for data-poor basins, as we can pre-train models on areas where there are copious amounts of data and then subsequently fine-tune them using the scarce data available for the target basin. This in particular seems like a promising direction for applying data-driven models to predictions on ungauged basins.

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A Training Procedures

We train the EA-LSTM models using the open-source code\(^2\) of Kratzert et al. for 30 epochs on NVIDIA P100 Pascal and V100 Volta GPUs using Python 3.7.3, PyTorch 1.1.0, and CUDA 9.0. The initial learning rate of 0.001 reduces to 0.0005 after ten epochs and to 0.0001 after another ten epochs. We feed batches of 256 samples into the network, which consists of one 256-neuron hidden layer with a dropout rate of 0.4.

For XGBoost,\(^3\) we use the same Python version and train on Intel Xeon E5-2683 v4 CPUs. To find suitable hyperparameters, we perform two three-fold cross-validated random searches on six training years and 53 basins. Both searches fit up to 100 trees at a learning rate of 0.25 and stop after 50 rounds without improvement. First, we search for good tree parameters (maximum tree depth, minimum child weight, column sampling, gamma) in 5000 random samples. Next, we use the found parameters in a 100-iteration random search to find regularization parameters (alpha, lambda). Table 2 lists the final hyperparameters. After parameter tuning, we train the XGBoost models on varying amounts of data at a learning rate of 0.08 for up to 20 000 iterations; however, we stop once the NSE-loss on a validation set of 10% of the training data does not improve for 100 rounds.

Table 2: Final XGBoost hyperparameters

| Parameter                  | Value  |
|----------------------------|--------|
| n_estimators               | 20 000 |
| early_stopping_rounds      | 100    |
| learning_rate              | 0.08   |
| max_depth                  | 6      |
| min_child_weight           | 1      |
| colsample_bytree           | 0.400  |
| colsample_bylevel          | 0.968  |
| gamma                      | 1.005  |
| reg_alpha                  | 18.944 |
| reg_lambda                 | 3.704  |
| subsample                  | 0.9    |

\(^2\)Git version 2dd199e. https://github.com/kratzert/ealstm_regional_modeling

\(^3\)Git version 96cd7ec. https://github.com/dmlc/xgboost