Advances In Uncertainty-Guided Local Climate Zone Classification

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Uncertainty Quantification

In the machine or deep learning context, we generally distinguish between two types of uncertainties:

- Aleatoric or data uncertainty inherent in the data
- Epistemic or model uncertainty, which reflects the model's confidence in its prediction

While the aleatoric uncertainty cannot be reduced, because it belongs to the data by nature, epistemic uncertainty can be reduced by finding more suitable machine learning algorithms or by modeling the data in a more clever way.

On a very broad level, we can separate two major streams of uncertainty quantification methods:

- Probabilistic methods including ensembles of networks or machine learners, dropout mechanisms, and Bayesian Neural Networks
- Deterministic approaches such as Prior Neural Networks (Malinin, Gales 2018), distance-preserving hidden mappings or spectral normalized networks

Why modeling uncertainties? Ideally, a high predictive uncertainty indicates lack of knowledge or confidence in the prediction. This can hint at an out-of-distribution or an expressive new data point. The latter can be a promising candidate which could be added to the initial data set and help the model to generalize better to unseen data.

Local Climate Zones (LCZs)

The 17-class scheme of Local Climate Zones (LCZs) as defined by (Stewart, Oke 2011) consists of 10 urban and 7 vegetation zones and describes urban conglomerates. Early works using LCZ maps have focussed on:

- Urban Heat Island (UHI) detection
- Urban planning
- Climatological applications

Human Label Uncertainty

For the data set SooSat LCZ42 (Zhu et al. 2020), we study a subset which was created to measure label confidence and has 1-10 label votes for each image. From the individual votes \( Y_i \), \( i = 1, \ldots, V \), belonging to classes \( k = 1, \ldots, K \), we can formulate vote counts:

\[
Y_{ik} = \sum_{i \in I_k} Y_i
\]

These are combined to a label with distributional form:

\[
\pi(Y_k) = \frac{1}{K!} \sum_{\theta \in \Theta} \theta(Y_k) \prod_{i=1}^{V} \theta(Y_i)
\]

The studied subset covers 10 European cities. Below, we look at the inherent human label uncertainty:

![Image](https://via.placeholder.com/150)

Uncertainty in feature space:

We show the results of the comparison between the regular model (one-hot labels based on majority vote, cross-entropy loss) and the distributional approach outlined above.

Conclusion & Outlook

- We have observed strong generalization and calibration performance when including human uncertainty
- Uncertainty quantification in the feature space is very promising, good results already for simple approach with single-class uncertainties

Outlook:

- More suitable loss functions and distance measures
- Link model uncertainty with human label uncertainty
- Use Bayesian reasoning to learn parameters of continuous distributions

References


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