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Assessing Predictive Uncertainties in Remote Sensing Image Classification via Conformal Prediction

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Conformal Prediction in a Nutshell

- Conformal Prediction (**CP**) is a **post-hoc** calibration method with theoretical **coverage guarantees**
- Applied to a classification model, the CP framework yields so-termed **prediction sets** (subset of all available classes)
- After *conformalization*, the true class is supposed to lie in the prediction set with a prespecified probability

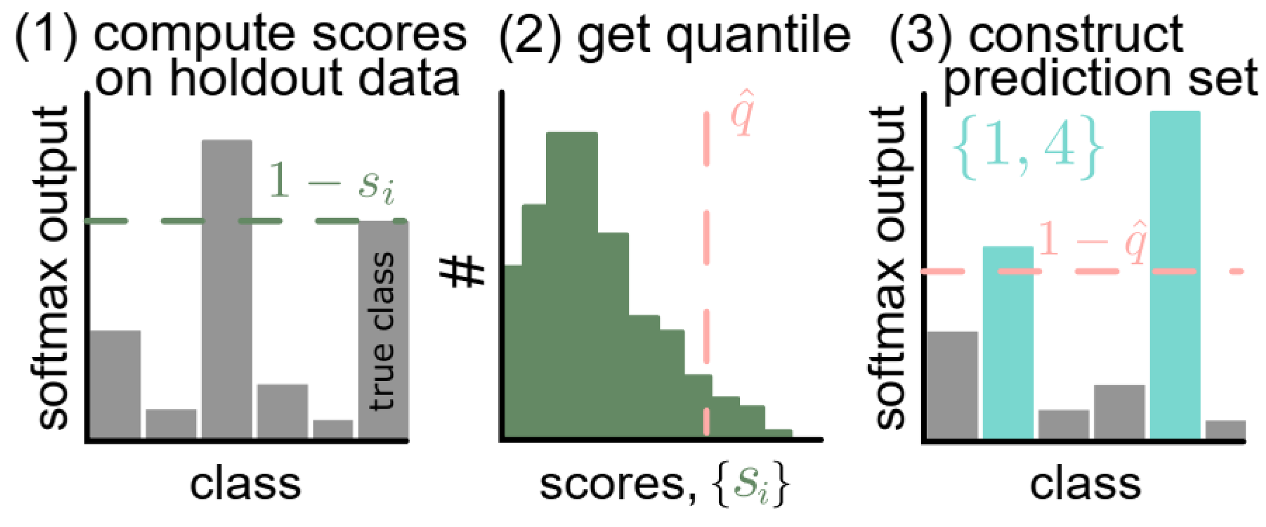
How it works:

- Choose an error rate $\alpha \in [0,1]$ and set aside a calibration dataset of size n_{calib}. The prediction set $\mathcal{C}(X_{test}) \subset \{1, \dots, K\}$ for a test data point X_{test} then should satisfy:

$$1 - \alpha \leq \mathbb{P}(Y_{\text{test}} \in \mathcal{C}(X_{\text{test}})) \leq 1 - \alpha + \frac{1}{n+1}$$

- Define the *conformal score* as 1 minus the softmax probability of the true class: $s_i = 1 - \hat{f}(X_i)_{Y_i}$
- Now set $\hat{q}$ as the $\lceil (n+1)(1-\alpha) \rceil$ / n quantile of $s_1, \dots, s_{n_{calib}}$
- Finally, create a prediction set for a new point as follows

$$\mathcal{C}(X_{\text{test}}) = \{y : \hat{f}(X_{\text{test}})_y \geq 1 - \hat{q}\}$$

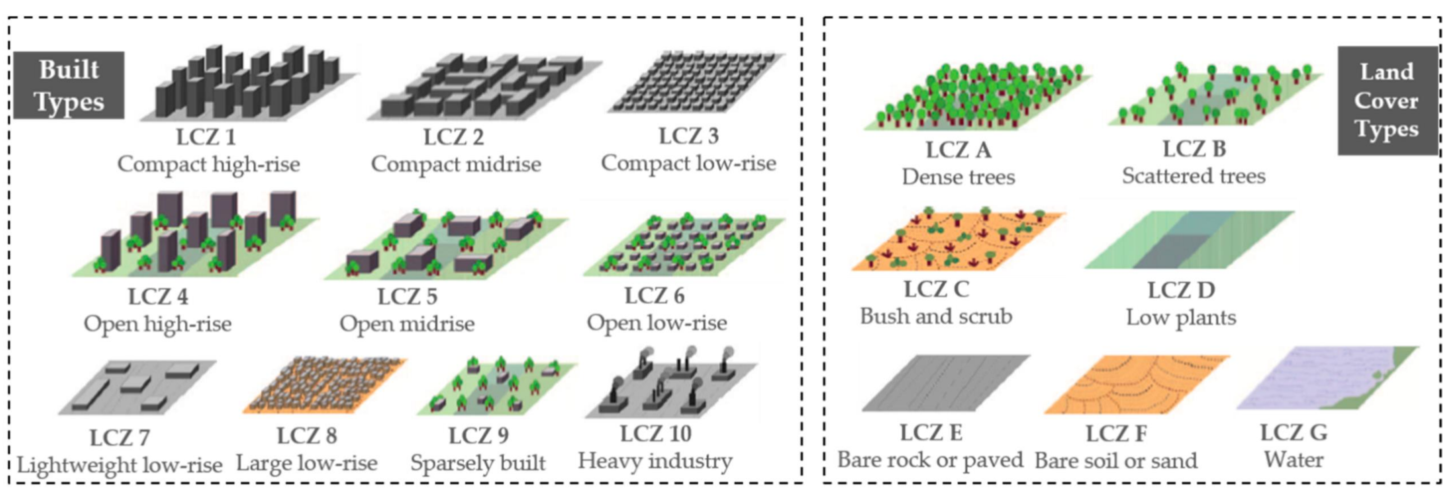


LAC Algorithm explained (Angelopoulos, Bates 2021)

Label Uncertainty in Remote Sensing

We study a subset of the *So2Sat LCZ42* (Zhu et al. 2020) dataset: **10 European cities** labeled by 10 remote sensing experts.

- Can CP help to derive suitable prediction sets with coverage guarantees being met?
- Are the prediction sets covering the human label uncertainty?



Local Climate Zone (LCZ) classification scheme (Zhao et al. 2019)

(Regularized Adaptive) Prediction Sets

We investigate multiple **CP** methods for the Urban classes (1-10):

- **Least Ambiguous set-valued Classifier (LAC):** Algorithm left
- **Naive approach**: Softmax values are ranked and summed up until the threshold is reached
- **Adaptive Prediction Sets (APS):** Softmax scores are summed up until true label is reached, last label can be in- or excluded or randomly decided (based on uniform sampling)
- **Regularized Adaptive Prediction Sets (RAPS):** APS with regularization hyperparameters based on *tuning dataset*
- **Top-k:** Fixed prediction set size based on rank of true label

Name	α Value	Coverage		No. of Null Sets		Avg. Pred. Set Size		Label Votes Cov.	
		One-Hot	Distr.	One-Hot	Distr.	One-Hot	Distr.	One-Hot	Distr.
Naive	$\alpha = 0.05$	77.5%	86.9%	0	0	**1.52**	2.20	56.8%	72.0%
	$\alpha = 0.1$	74.3%	82.0%	0	0	**1.30**	1.72	53.1%	64.4%
	$\alpha = 0.15$	72.8%	78.4%	0	0	**1.19**	1.47	50.9%	59.6%
	$\alpha = 0.2$	71.7%	76.1%	0	0	**1.12**	1.30	49.3%	55.8%
LAC	$\alpha = 0.05$	94.4%	95.0%	0	0	3.31	3.52	81.5%	86.0%
	$\alpha = 0.1$	89.1%	89.7%	0	0	2.37	2.43	69.0%	77.0%
	$\alpha = 0.15$	84.0%	84.5%	0	0	1.85	1.83	62.6%	67.6%
	$\alpha = 0.2$	79.4%	79.8%	0	2	1.48	1.41	57.7%	58.7%
APS w/ last label	$\alpha = 0.05$	95.6%	96.1%	0	0	3.75	3.83	86.3%	87.9%
	$\alpha = 0.1$	91.7%	**92.5%**	0	0	2.73	2.92	73.3%	**81.7%**
	$\alpha = 0.15$	87.7%	89.5%	0	0	2.22	2.39	67.2%	76.3%
	$\alpha = 0.2$	84.7%	**86.8%**	0	0	1.93	2.05	63.6%	**71.5%**
APS w/o last label	$\alpha = 0.05$	90.6%	91.6%	0	0	2.89	2.90	74.5%	80.1%
	$\alpha = 0.1$	82.8%	85.8%	0	0	1.97	2.07	62.9%	70.2%
	$\alpha = 0.15$	77.8%	80.6%	0	0	1.54	1.61	57.2%	62.4%
	$\alpha = 0.2$	75.0%	77.1%	0	0	1.33	1.38	53.8%	57.5%
APS w/ randomness	$\alpha = 0.05$	94.7%	94.5%	3	9	3.44	3.46	82.4%	85.1%
	$\alpha = 0.1$	89.3%	89.6%	20	55	2.47	2.57	69.8%	77.3%
	$\alpha = 0.15$	83.6%	84.5%	99	149	1.96	2.01	63.2%	69.5%
	$\alpha = 0.2$	78.5%	79.4%	236	296	1.66	1.69	58.3%	62.8%
RAPS	$\alpha = 0.05$	94.8%	94.9%	2	2	3.54	3.51	84.3%	86.0%
	$\alpha = 0.1$	89.4%	89.8%	2	22	2.59	2.56	70.9%	77.5%
	$\alpha = 0.15$	83.8%	85.1%	66	106	1.95	2.04	62.9%	70.5%
	$\alpha = 0.2$	78.9%	80.2%	106	151	1.57	1.66	57.7%	63.2%
Top-k	$\alpha = 0.05$	**96.6%**	95.6%	0	0	5	4	**93.1%**	88.8%
	$\alpha = 0.1$	90.5%	91.0%	0	0	3	3	75.6%	80.3%
	$\alpha = 0.15$	90.5%	**91.0%**	0	0	3	3	75.6%	**80.3%**
	$\alpha = 0.2$	83.4%	82.3%	0	0	2	2	64.3%	66.6%

Results for various methods on LCZ42 Evaluation Dataset (https://mediatum.ub.tum.de/1659039). Validation dataset was used for calibration. Coverage = True label in prediction set. Sen2LCZ (Qiu et al. 2020) was used as network classifier for the Urban classes. One-Hot = Training with single label (majority vote of experts), Distr. = Training with empirical distribution of label votes. Label Votes Cov. = Percentage of expert label votes covered by prediction sets.

Findings

- Naive approach overconfident; bad coverage despite small sets
- Strong results with APS, regularization seemingly without effect
- Randomization leads to large no. of null sets
- Top-k conformalization shines with seemingly great results, but comes with comparably large prediction sets
- Strong performance increase with distributional label approach

References:

- Angelopoulos, A. N., & Bates, S. (2021). A gentle introduction to conformal prediction and distribution-free uncertainty quantification. arXiv preprint arXiv:2107.07511.
- Qiu, C. et al. (2020). Multilevel feature fusion-based CNN for local climate zone classification from sentinel-2 images: Benchmark results on the So2Sat LCZ42 dataset. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13.
- Zhao, N., Ma, A., Zhong, Y., Zhao, J., & Cao, L. (2019). Self-training classification framework with spatial-contextual information for local climate zones. Remote Sensing, 11(23).
- Zhu, X. X. et al. (2020). So2Sat LCZ42: A benchmark data set for the classification of global local climate zones. IEEE Geoscience and Remote Sensing Magazine, 8(3).

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