Optimal Sensor Placement for Black Carbon AOD with Convolutional Neural Processes

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Introduction

- **Black carbon** (BC) aerosols
  - Strong warming effect due to radiation absorption
  - High uncertainty due to lack of global-scale observations
- The Aeronet network of **ground-based sensors**
  - Primary source of aerosol absorption optical depth (AAOD) measurements
  - But spatially sparse and temporally intermittent

Research Questions

→ How to model BC AOD from sparse observations?

→ Where to place new sensors to maximise informativeness?

- **Convolutional Neural Processes** (ConvNPs)
  - Learn to map from heterogeneous context sets to probabilistic predictions
  - Use in active learning context to evaluate optimal observation locations[1]

Data and implementation

Goals

- Use ConvNPs to model daily BC AOD over Europe from limited observations
- Minimise uncertainty in the predictive function by proposing new sensor placements

Data

- *Ground truth:* CAMS reanalysis of atmospheric composition[2]
- *Context:* Off-grid samples of BC AOD, gridded wind, auxiliary space-time coordinate variables
- *Target:* Gridded daily-average BC AOD
- *Tasks:* BC AOD observations provided at random points (training) or at existing stations (evaluation)
- The Aeronet network's 296 stations in Europe[3] serve as initial sensor locations

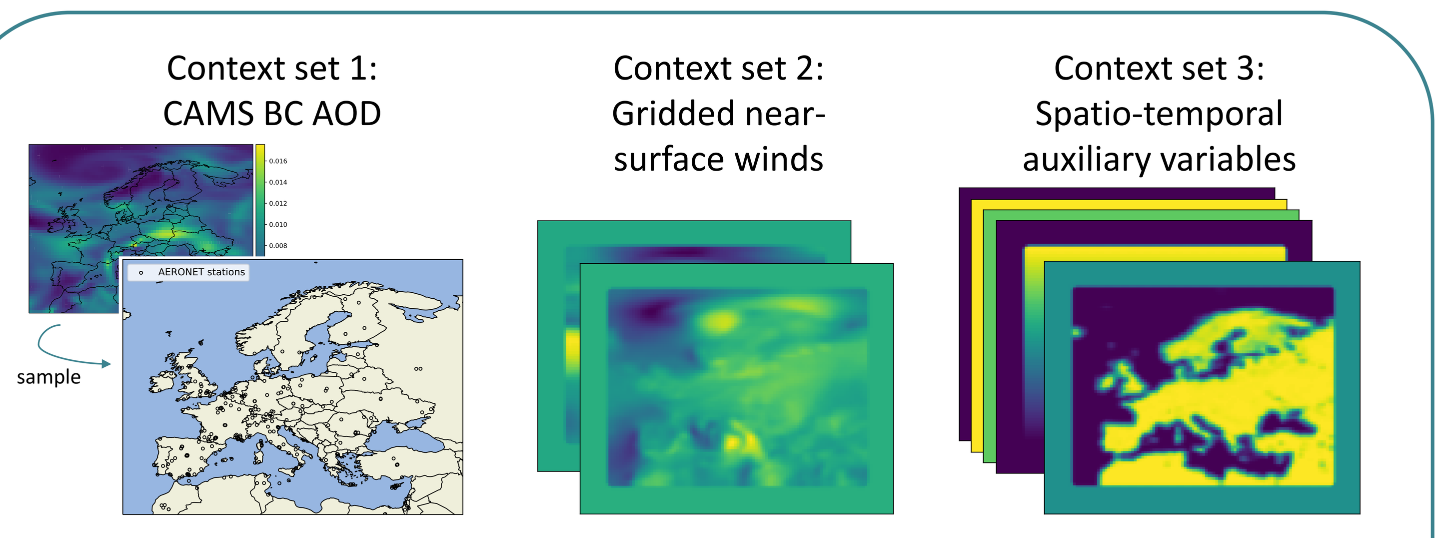
The ConvNP models and the sensor placement experiments are implemented using **DeepSensor**[4] – an open-source Python package for modelling environmental data with neural processes

Convolutional Neural Processes

ConvNPs meta-learn a mapping from context data $C = \{x_i^{(c)}, y_i^{(c)}\}_i^{N_c}$ and target inputs $x^{(t)}$ to Gaussian predictions over target outputs $y^{(t)}$

Training: Minimise negative log-likelihood of true $y^{(t)}$ under the predicted Gaussian from limited randomly sampled context observations

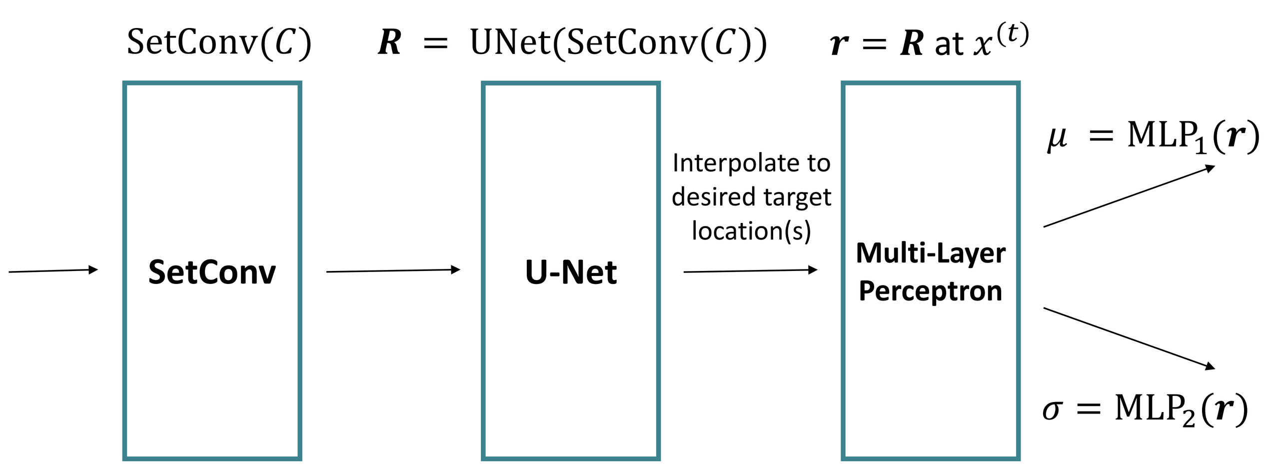
Context datasets C



Point observations of the target variable

Additional explanatory information

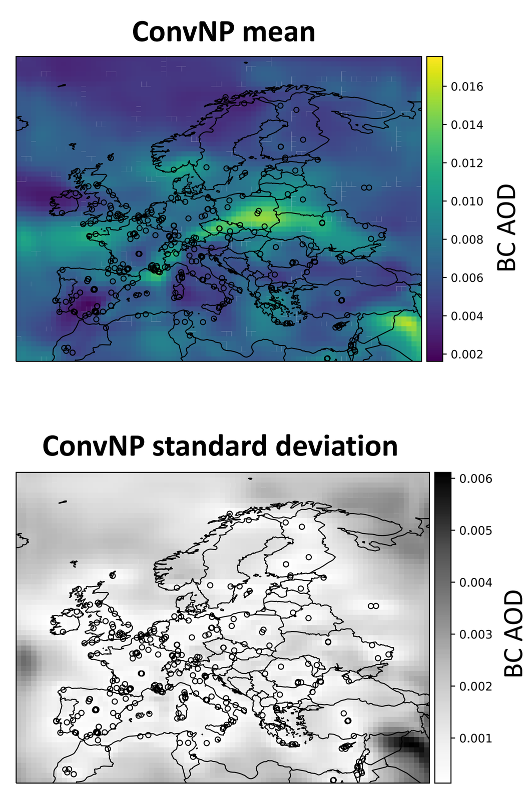
Enable non-stationarity



- Handles different spatial scales and missing data
- Encodes context sets to a common grid

- Flexible convolutional neural network
- Extracts feature representation of the context set

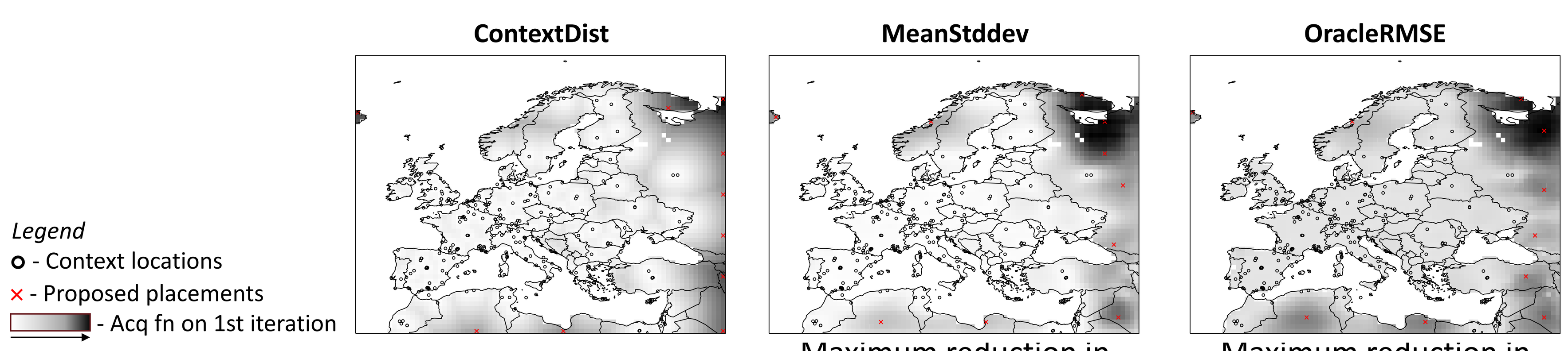
- Outputs predictive mean and standard deviation at the target location



Sensor Placement Experiments

Active learning for sensor placement

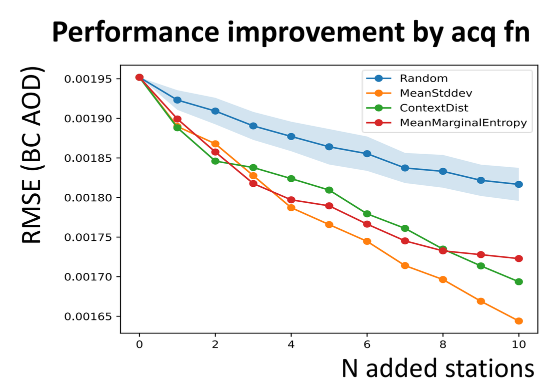
- Acquisition function evaluates the search space for the expected information gain of a new observation
- Greedy algorithm averages the function over several tasks and proposes next optimal placement

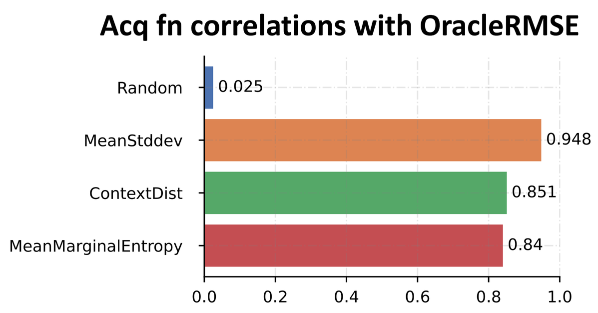


Farthest distance heuristic

Maximum reduction in average model uncertainty

Maximum reduction in average model error (seeing ground truth)

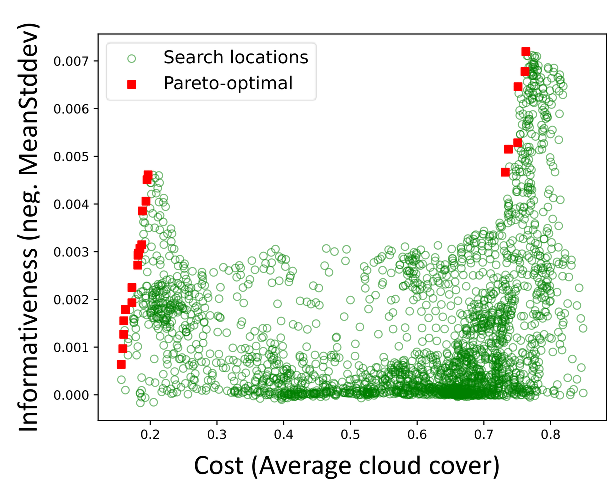


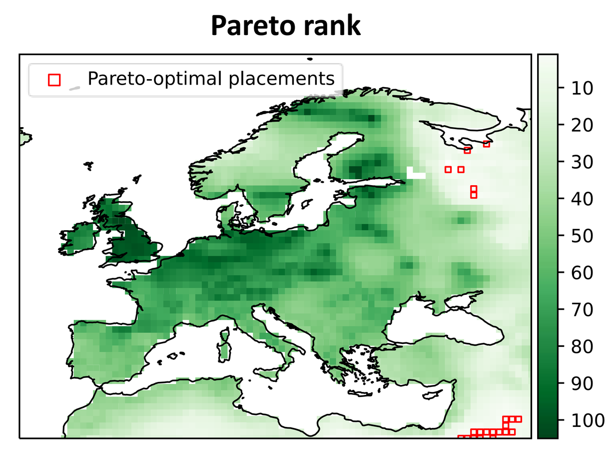


- High correlation of MeanStddev with Oracle version validates it as informativeness criterion

Multi-objective Pareto optimisation

- In a real-world scenario, must trade off expected informativeness and practical costs of potential sensor locations
- Consider the cost of missed AOD measurements due to cloud cover
- Find Pareto-efficient solutions, where informativeness cannot be improved without worsening the costs and vice versa





Discussion

- ConvNPs learn to model the BC AOD field from limited observations
- Informative sensor placements are obtained by leveraging the ConvNPs' probabilistic predictions
- Higher-resolution "ground truth" might be needed to better capture AOD spatial variability and uncertainty

Next steps

- Test the Gaussian ConvNP variant, which models the output distribution jointly and incorporates spatial covariance
- Fine-tune the models using real sensor data[5] from Aeronet
- Incorporate cloud cover and measurement availability considerations in the sensor placement experiments

References and Acknowledgements

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