Novel Geo-spatial Interpolation Analytics for General Meteorological Measurements

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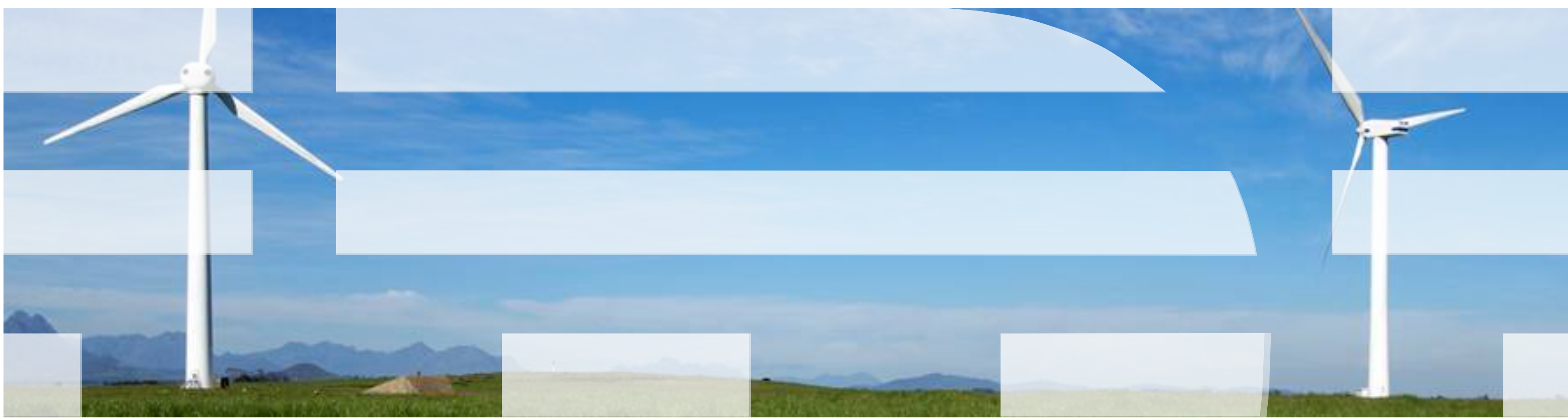

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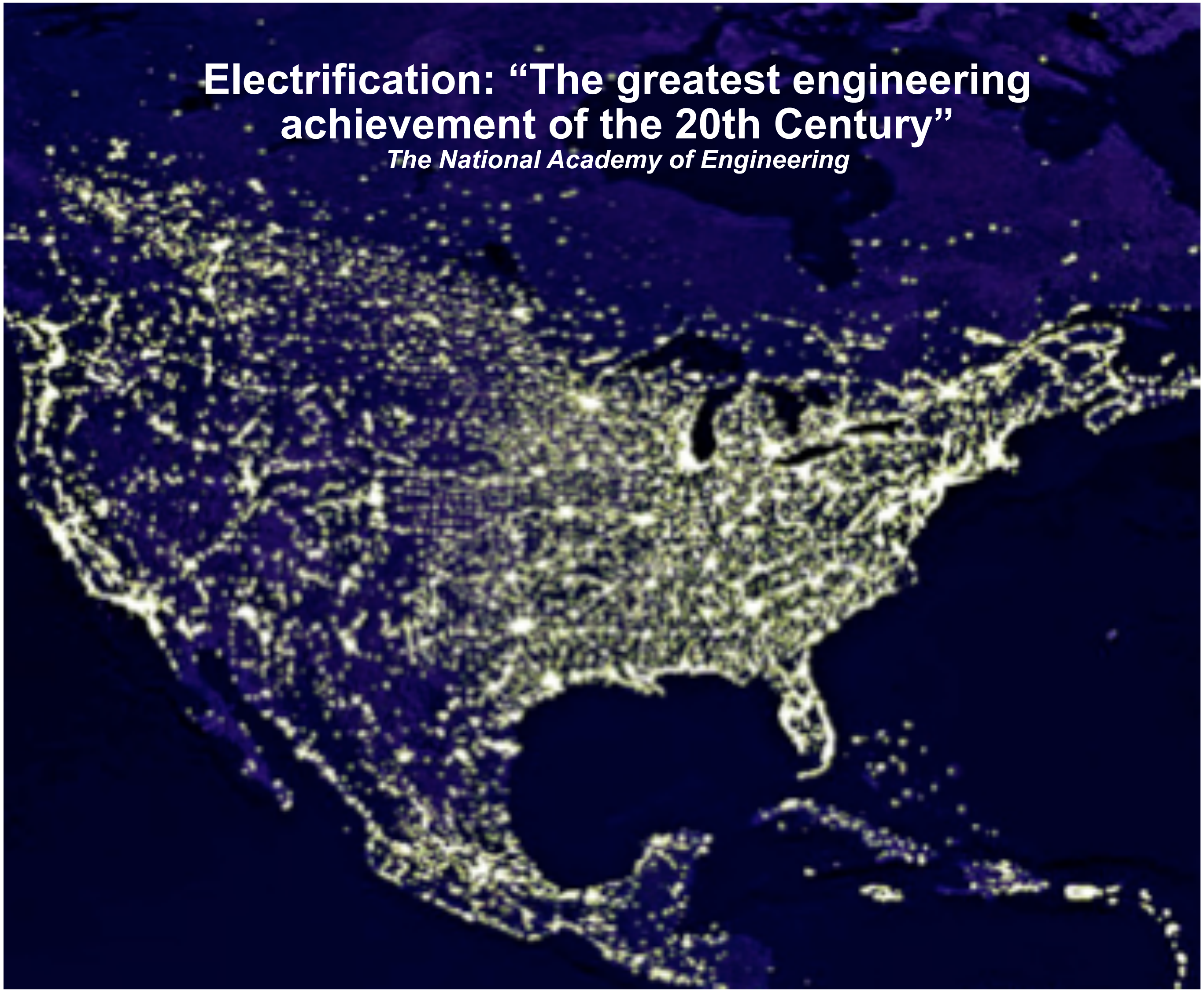
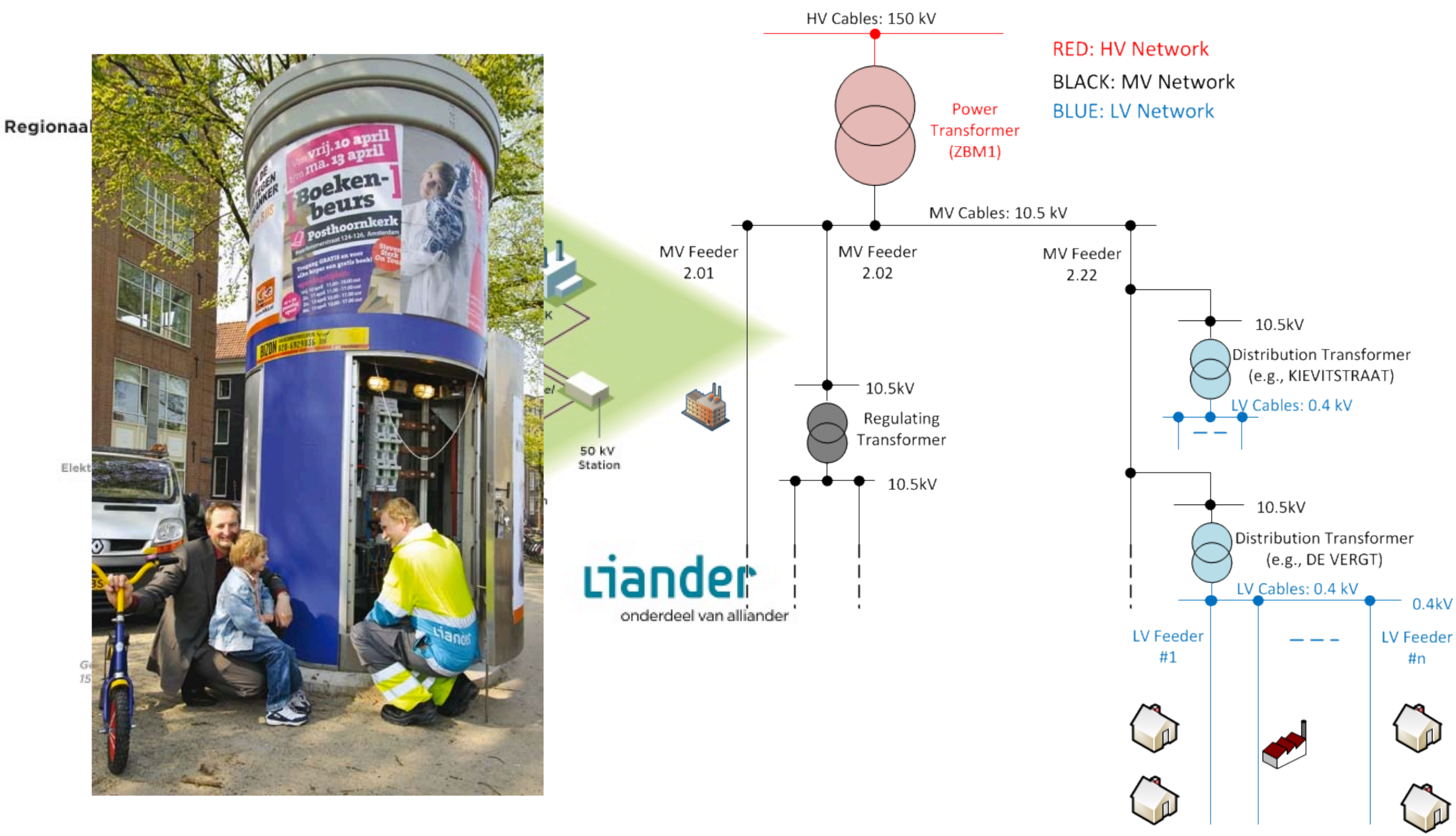


Electrical (Power) Engineering101



Electric Utility is a Capital Intensive Industry

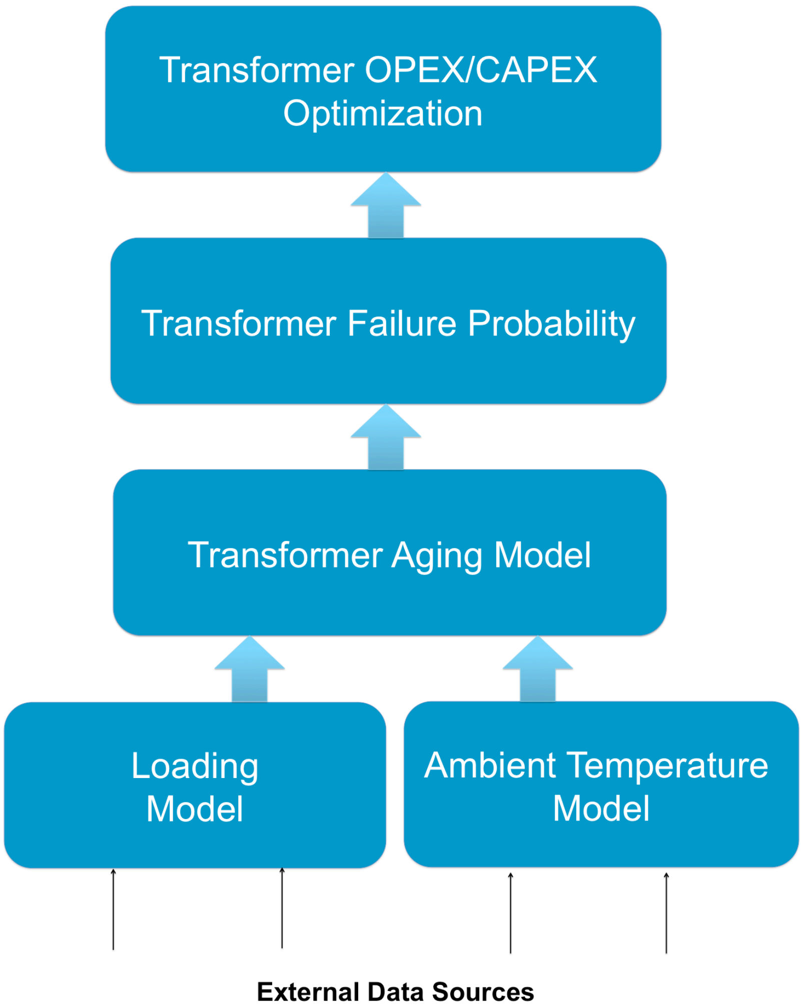
Much more Distribution Transformers than Power Transformers

Optimal Asset Maintenance and Capital investment is of Importance

- Existing asset maintenance largely depends on pre-determined “rule-of-thumb” schedules
  - Does not consider the realistic utilization impacts
  - Can be risky at both over- and under-maintenance
  - Incurs unnecessary cost for a utility
- Decision on capital investments for upgrades/replacement gets impacts too because of this

- Maintenance schedule should reflect true utilization of individual assets
- One of the key components to enable this is to compute the “Electrical Age” of transformers

But How to Obtain Ambient Temperature of Transformers?



Challenge: there are only Limited Number of Weather Stations

Paucity of Weather Station Network is a Common Issue

- Meteorological metrics, such as temperature, wind speed, humidity and pressure, are useful for many applications
  - Smarter grids (Superstorm Sandy's caused outages)
  - Dynamics of forests
  - Cherry blossom
  - …

- For many business-related applications, it is more useful to have a finer resolution meteorological metrics, both spatially and temporarily, than provided by typical weather forecast service
  - NOAA: National Oceanic and Atmospheric Administration

- A solution for meteorological metrics at finer resolution was sought in this work

Physical-based Model is typically Computationally Intensive

- Weather Research and Forecasting (WRF) Model is most well-known and used by NCEP (National Centers for Environmental Prediction) and many other forecasting centers internationally
- A numerical weather prediction (NWP) system by solving a set of PDEs (e.g., compressible, nonhydrostatic Euler equation)

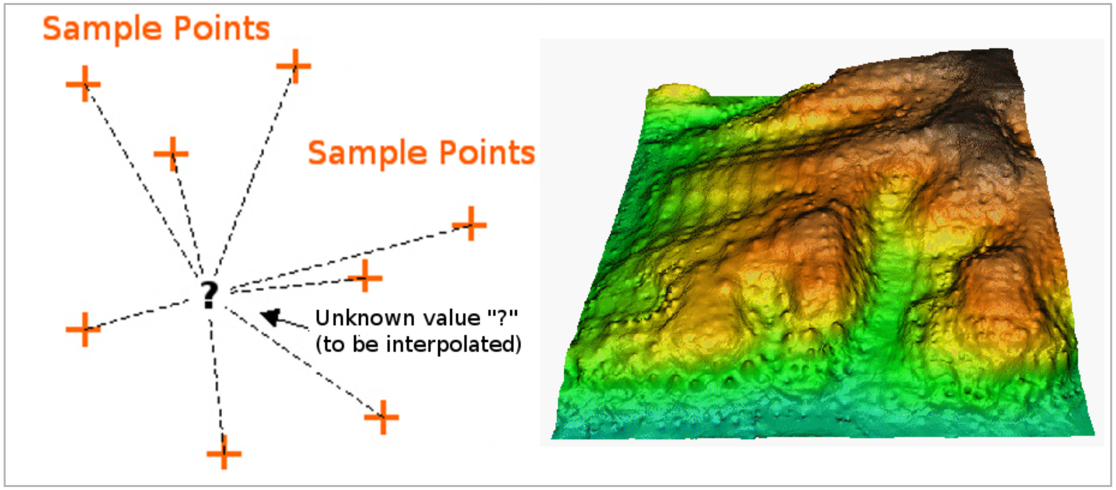
$$\begin{aligned}
\partial_t U + (\nabla \cdot \mathbf{V} u) - \partial_x (p \phi_\eta) + \partial_\eta (p \phi_x) &= F_U \\
\partial_t V + (\nabla \cdot \mathbf{V} v) - \partial_y (p \phi_\eta) + \partial_\eta (p \phi_y) &= F_V \\
\partial_t W + (\nabla \cdot \mathbf{V} w) - g(\partial_\eta p - \mu) &= F_W \\
\partial_t \Theta + (\nabla \cdot \mathbf{V} \theta) &= F_\Theta \\
\partial_t \mu + (\nabla \cdot \mathbf{V}) &= 0 \\
\partial_t \phi + \mu^{-1} [(\mathbf{V} \cdot \nabla \phi) - gW] &= 0
\end{aligned}$$

  – Formulated using a terrain-following mass vertical coordinate

- Accurate, but computationally expensive (HPC)
- Resolution is also limited by boundary conditions (e.g., provided by weather station measurements) without special treatment

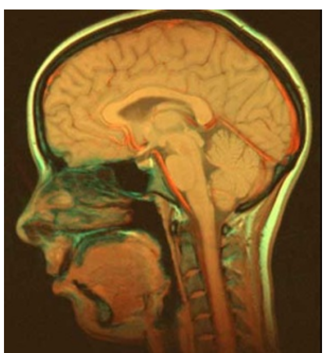
Learning-based Model: Trade-off between Accuracy and Speed

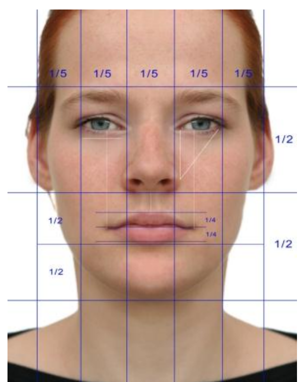
- Inverse distance weighting
- Splines, Regression, Kriging
- Neural networks and machine learning techniques

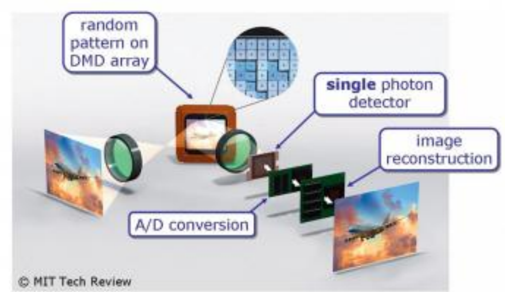


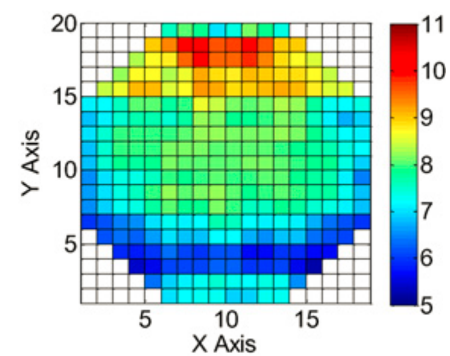
Major Contributions of this Work

- Application of Compressed Sensing (CS) to large-scale geospatial interpolation of climate data
  - Compressed Sensing (CS) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems.
- New Bayesian Compressed Sensing model with student-T prior (BCST)
- Efficient and effective estimation of latent variables for BCST
- Extensive experiments to validate the effectiveness of the proposed model





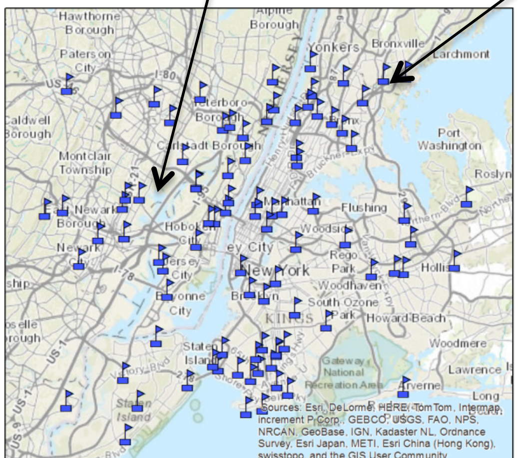


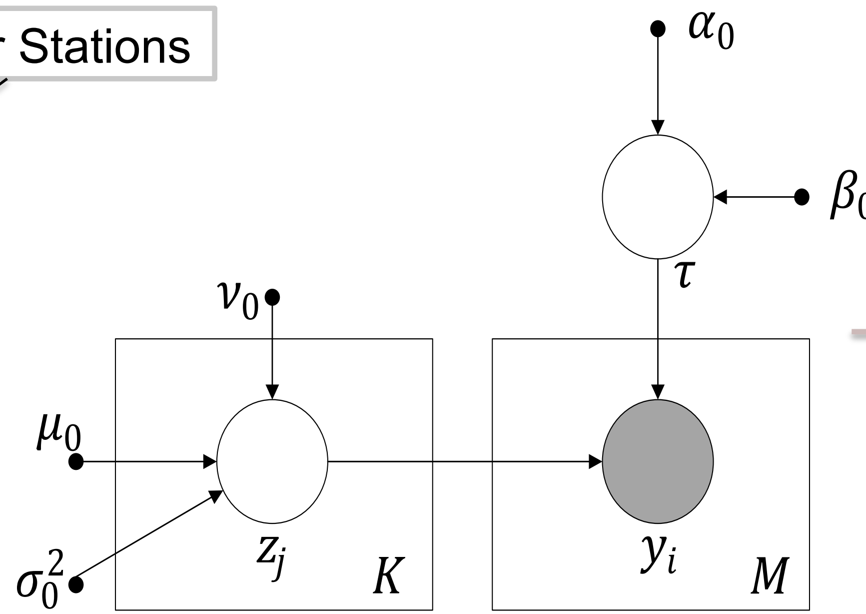


Estimate DCT Coefficients to Minimize Reconstruction Error with Student-t prior

Meteorological metrics?

Weather Stations

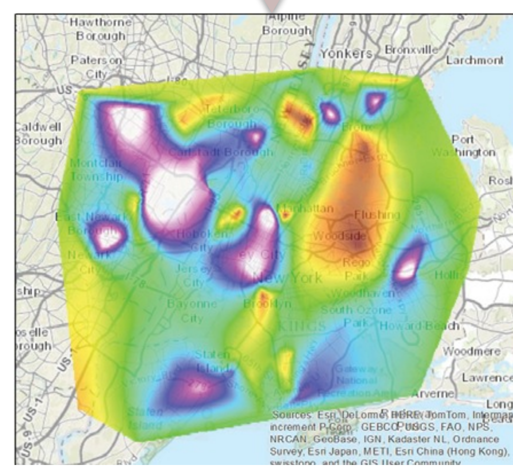




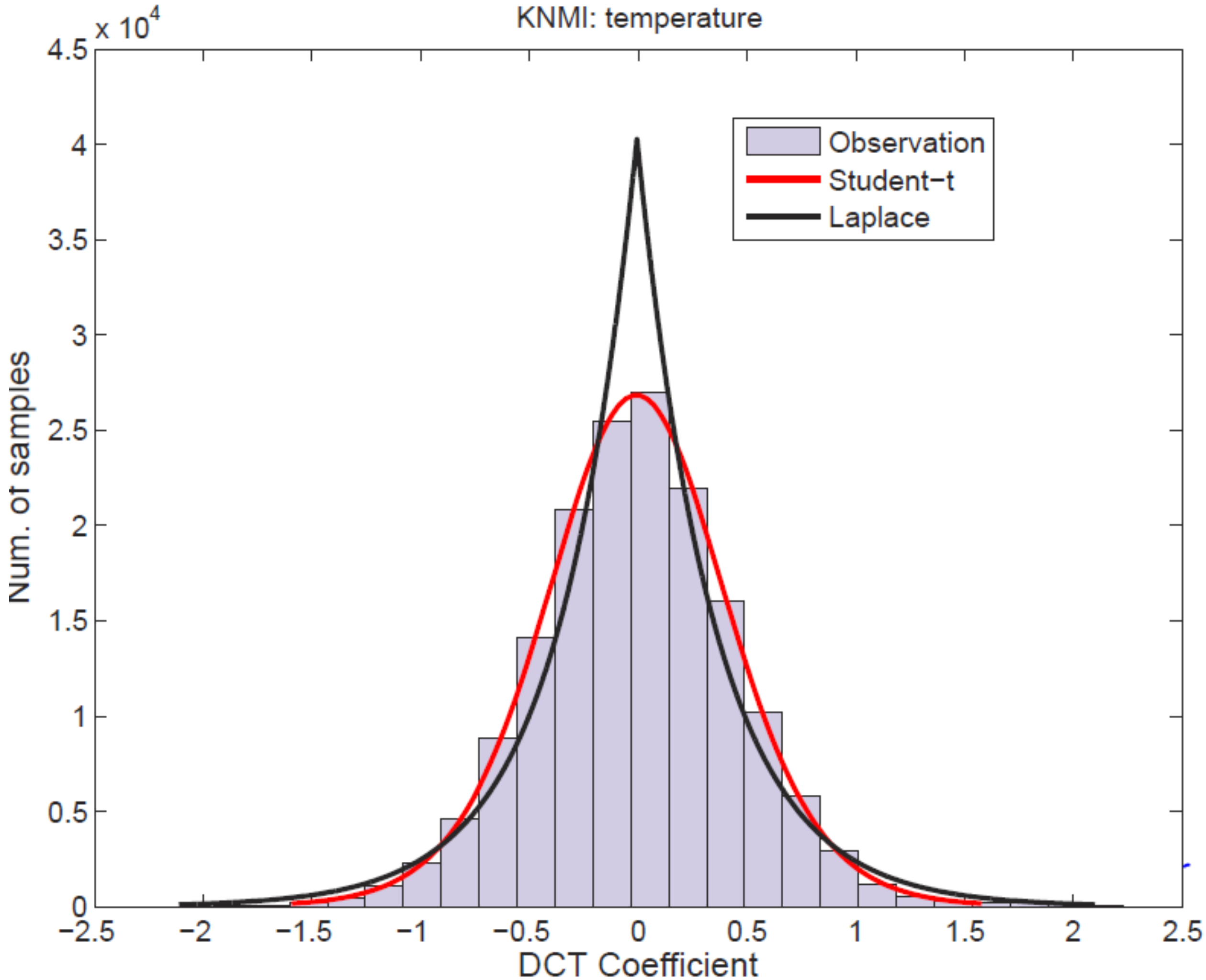
$$P(y_i \mid \mathrm{a}\mathbf{z}, \tau) = \mathcal{N}(y_i \mid \mathbf{\Phi z}, \tau^{-1})$$

$$P(z_j) = t_{\nu_0}(z_j \mid \mu_0, \sigma_0^2)$$

$$P(\tau) = \mathrm{Gamma}(\tau \mid \alpha_0, \beta_0)$$

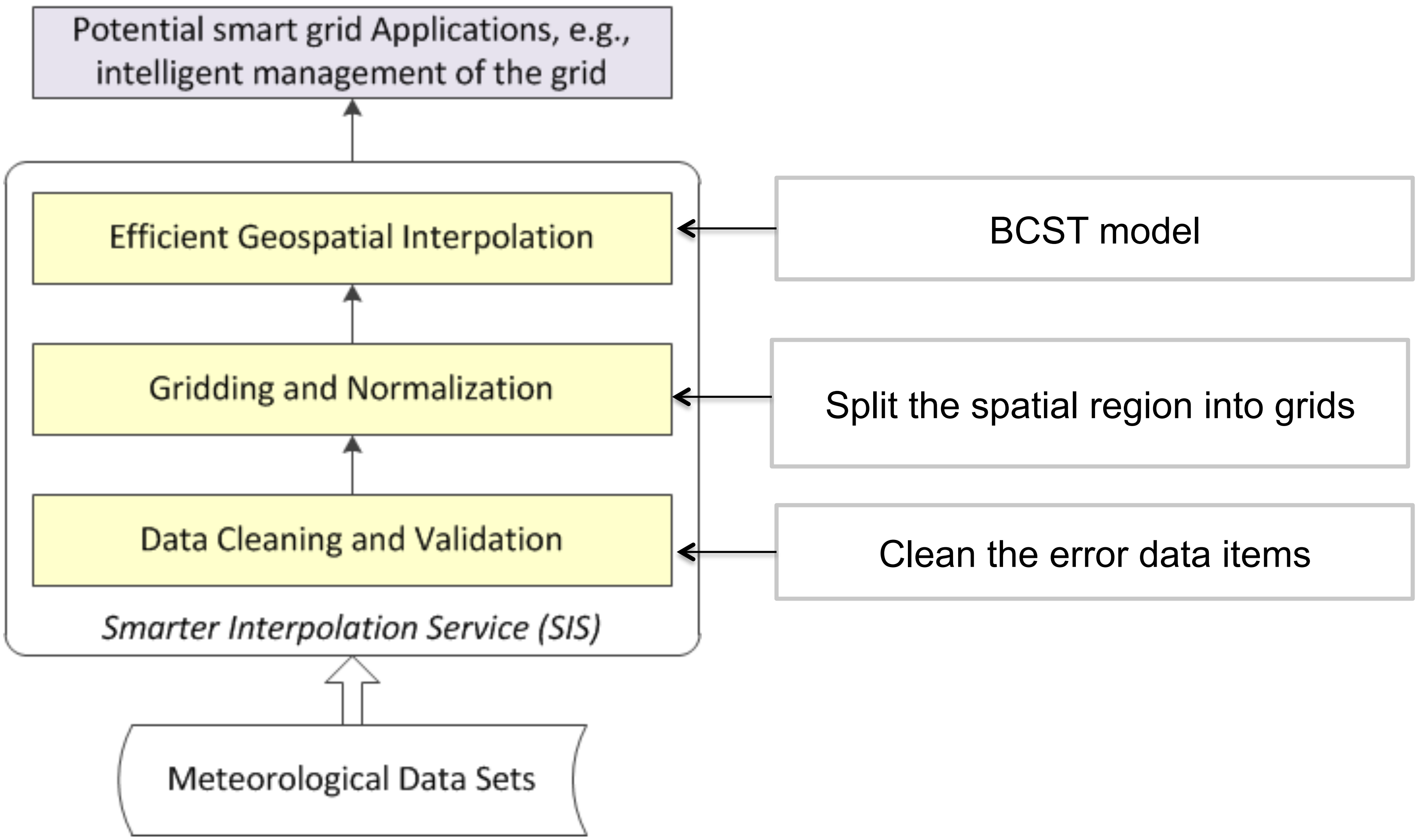


Student-t is a better Prior than Laplace for Meteorological Metrics



- Log-likelihood ratio (LLR) test to compare the fit of both priors
  – R = 4499.0
- How to derive an analytical form to efficiently do the prediction?
  – Approximated Variational Inference

BCST as a General Meteorological Interpolation Service



Experimental Setup

- Two data sets
  - KNMI (Royal Netherlands Meteorological Institute) daily weather data
    - 33 Weather stations in Netherlands
    - Temperature, humidity, average wind speed etc
    - Grid: ~25 KM, 11x17
  - Vendor provided 5-minute weather data
    - About 15K weather stations mainly in North America
    - Temperature, Humidity, Barometric pressure, etc
    - ~10 KM, 20x20
- Evaluation metric: average normalized error (ANE)
- Comparison methods
  - BCST-AVI (proposed method with Approximated Variational Inference)
  - BCST-GS (proposed method with MCMC Sampling for inference)
  - BCSL: compressed sensing with Laplace prior for DCT coefficients
  - CS: compressed sensing L1 norm to regularize DCT coefficients
  - TPS: Thin Plate Spline
  - UK: Universal Kriging

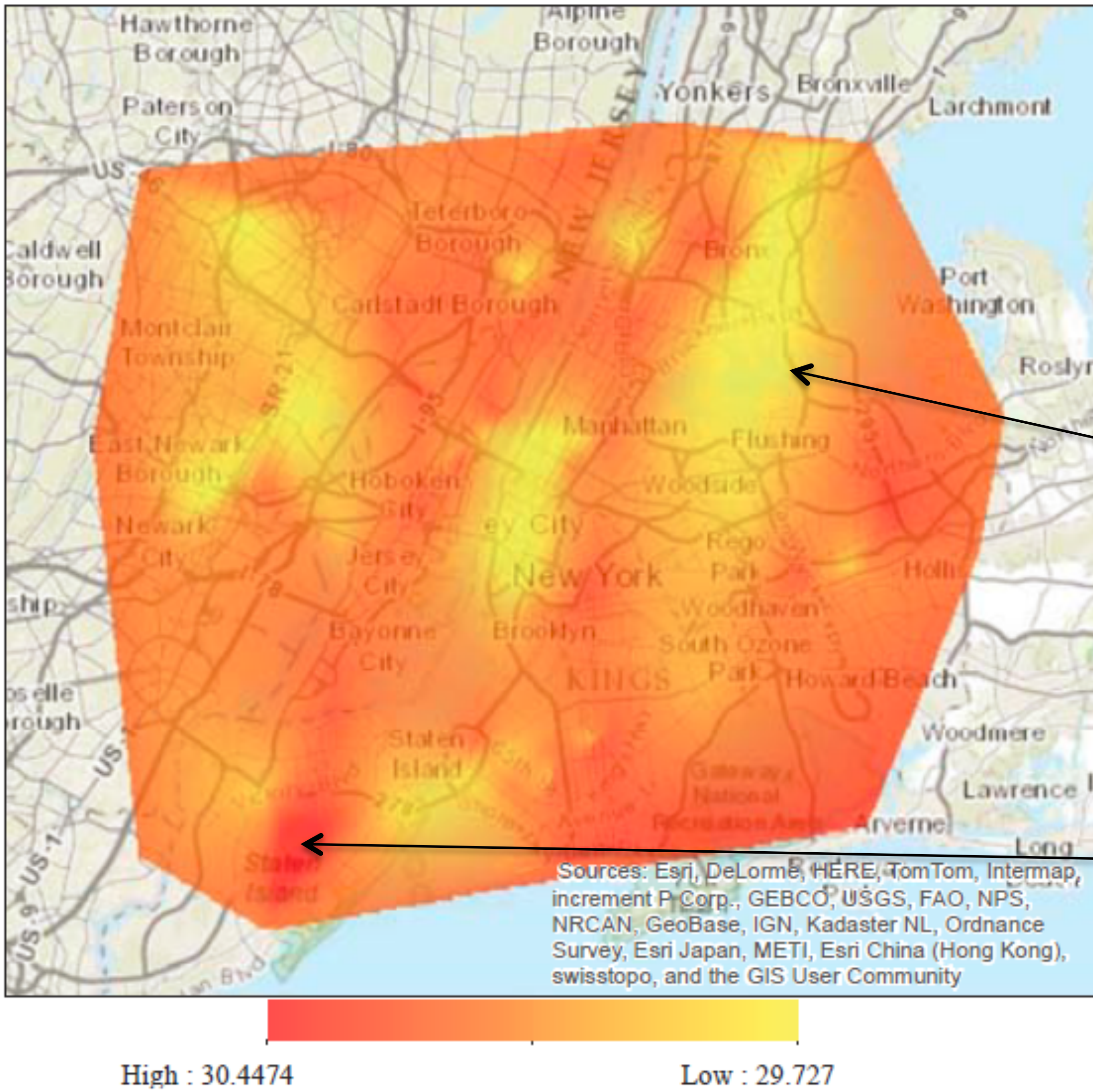
Temperature Interpolation Results on KNMI (metric: percentage)

Num. of Observations	BCST-AVI	BCST-GS	BCSL	CS	TPS	UK
6	**4.4655** $\pm$ 0.2090	4.5271 $\pm$ 0.2043	6.0500 $\pm$ 0.2360	6.5341 $\pm$ 0.2765	24.075 $\pm$ 1.0912	21.531 $\pm$ 1.2026
8	4.1963 $\pm$ 0.2071	**4.0133** $\pm$ 0.2058	5.5939 $\pm$ 0.2126	6.0756 $\pm$ 0.2391	15.071 $\pm$ 1.1238	14.295 $\pm$ 1.2815
10	3.9797 $\pm$ 0.2077	**3.9246** $\pm$ 0.2001	5.0283 $\pm$ 0.2247	5.7360 $\pm$ 0.2337	11.676 $\pm$ 1.0394	10.578 $\pm$ 1.2292
12	**3.8415** $\pm$ 0.2070	3.8518 $\pm$ 0.2085	4.9300 $\pm$ 0.2586	5.5593 $\pm$ 0.2274	10.209 $\pm$ 0.9548	8.0038 $\pm$ 0.9005
14	3.6969 $\pm$ 0.2041	**3.6728** $\pm$ 0.2097	4.5629 $\pm$ 0.2256	5.3472 $\pm$ 0.2199	8.3562 $\pm$ 0.4875	6.4566 $\pm$ 0.3853
16	3.4824 $\pm$ 0.2059	**3.4815** $\pm$ 0.2056	4.4169 $\pm$ 0.2698	5.1859 $\pm$ 0.4248	6.9671 $\pm$ 0.4248	5.2924 $\pm$ 0.4530

Runtime Comparison (in ms)

Model	KNMI Data	Vendor Data
BCST-AVI	$\mathbf{14.162} \pm 1.7789$	$\mathbf{31.169} \pm 2.0685$
BCST-GS	14205 ± 269.91	63375 ± 1792.7
BCSL	116.20 ± 3.1875	489.65 ± 12.750
CS	69.073 ± 30.499	276.31 ± 30.312
TPS	74.000 ± 6.6500	106.00 ± 8.4327
UK	50.000 ± 5.9470	160.00 ± 10.824

Example: Barometric Pressure Map in NYC



Metric: 1/100 inch of mercury

Low pressure

High pressure

Conclusions & Future Work

- A compressed sensing technique with Student-t prior
- Efficient and effective algorithms for both inference and learning
- Many potential applications, especially in the area of to smarter energy research

- Future work:
  - Considering both spatial and temporal correlations to improve resolution in both dimensions
  - Optimal gridding schemes