Machine Learning Models with Uncertainty Quantification for Precipitation Type Prediction

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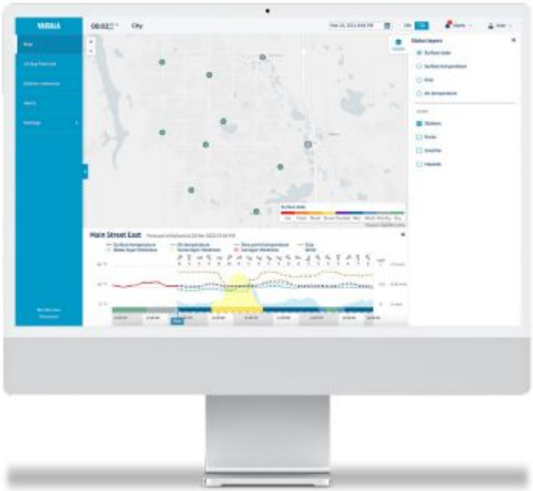
Precipitation type greatly affects impact of winter storms

Vaisala Wx Horizon Pro

Bring actionable insights and predictions to your winter road maintenance

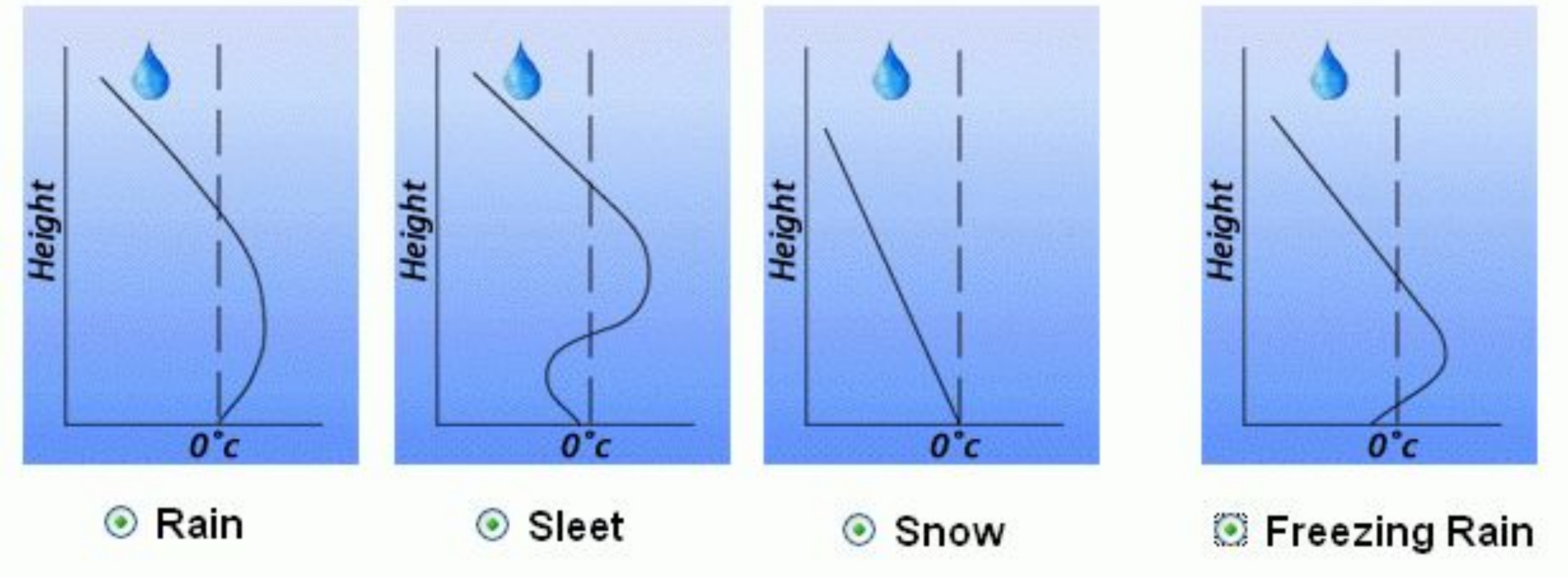


What did I do?

- Evaluated precipitation type models
  - map-reduce computations on large Xarrays (i.e. banging my head against the cluster)
- Extended Machine Learning Methods for Uncertainty Quantification
- Wrote a small utility for submitting PBS jobs in python (https://github.com/dkimpara/pbs_utils)

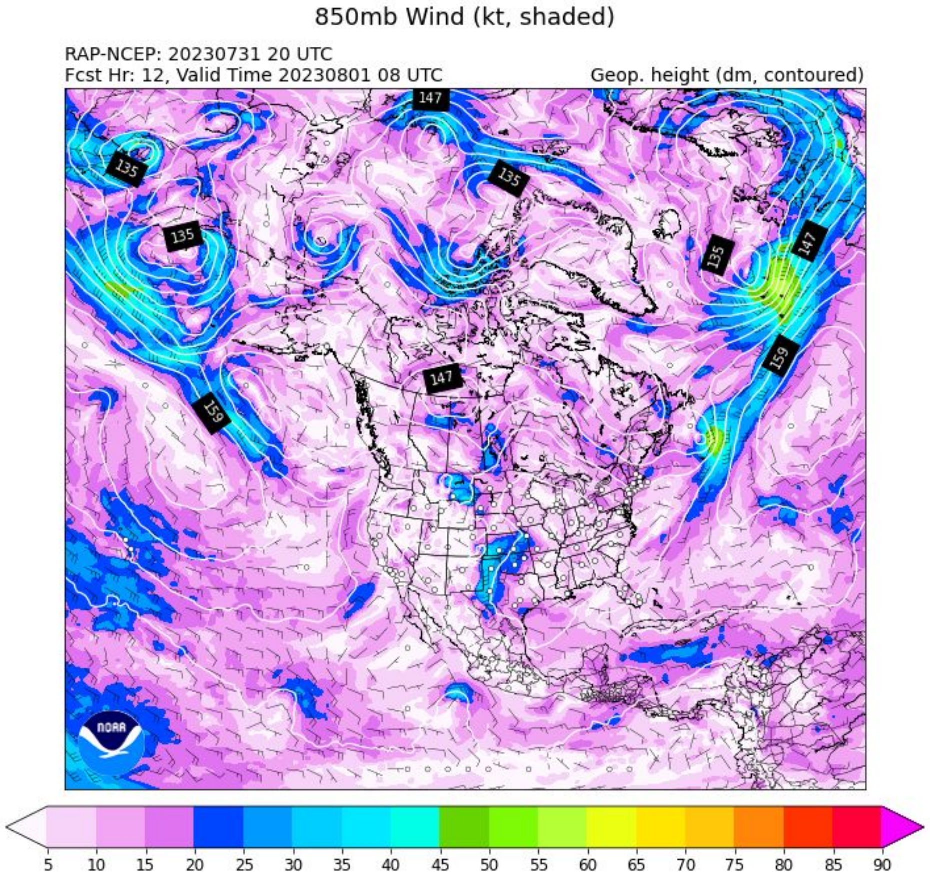
How do we predict precipitation type?

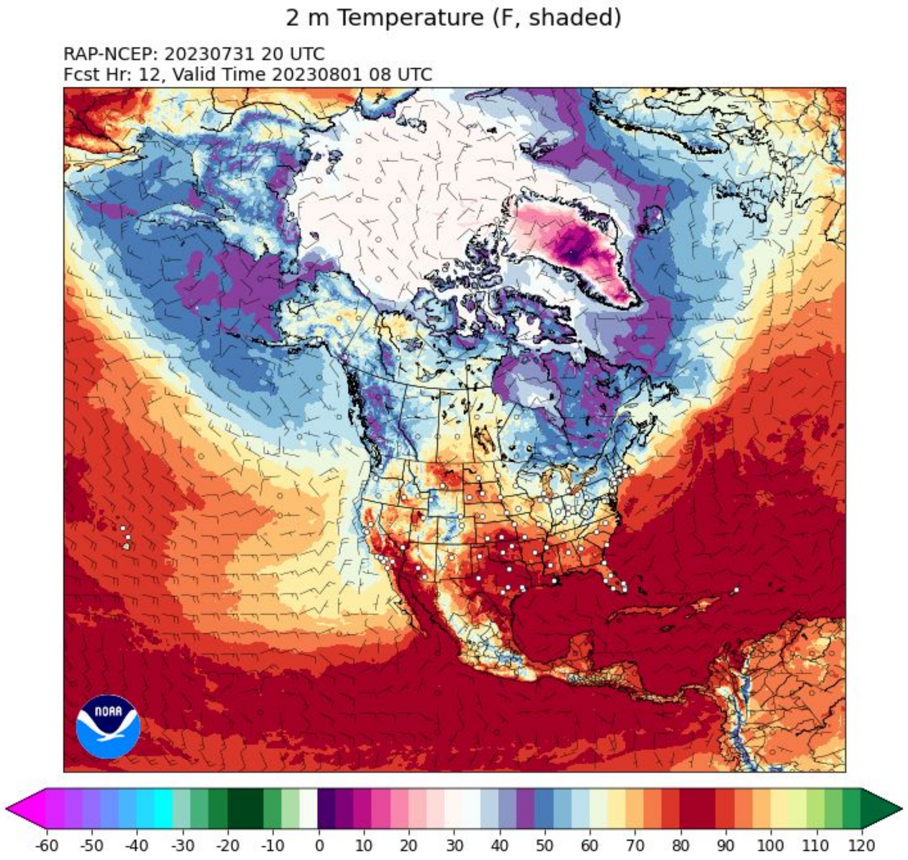
-> Profiles of atmospheric variables at each height (soundings):
- temperature
- dewpoint
- wind



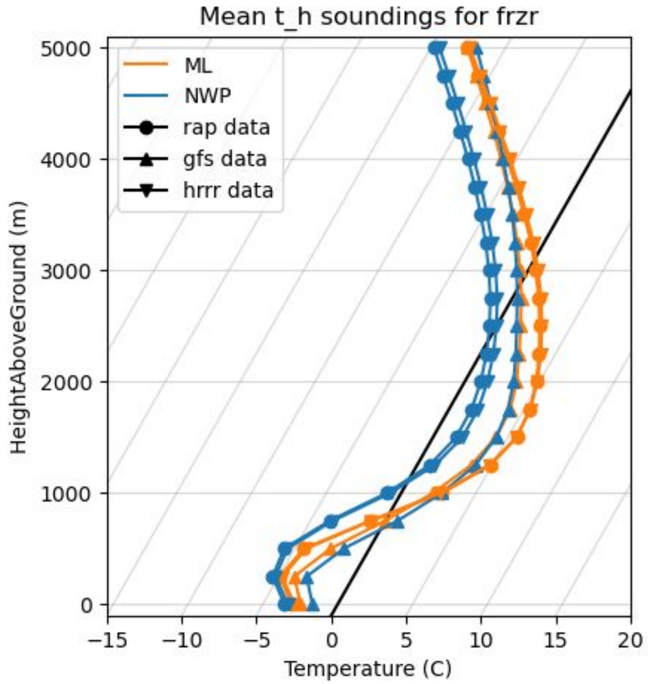
Where to get soundings?

Rapid Refresh (RAP) Model -> predictions for atmospheric variables

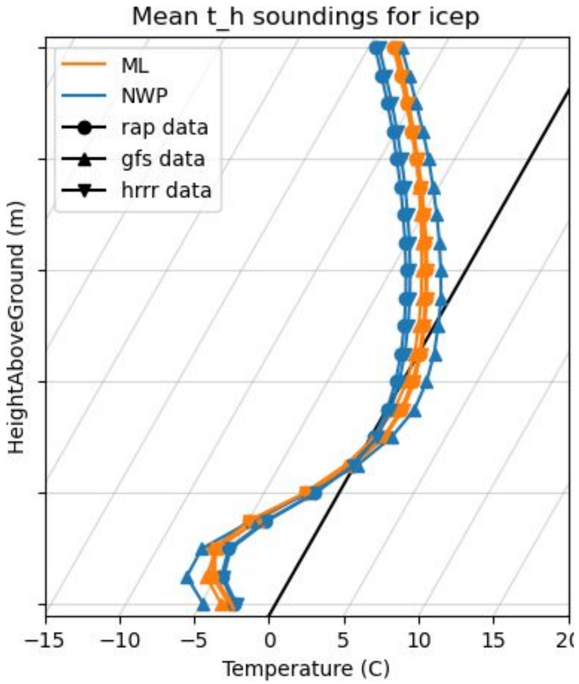




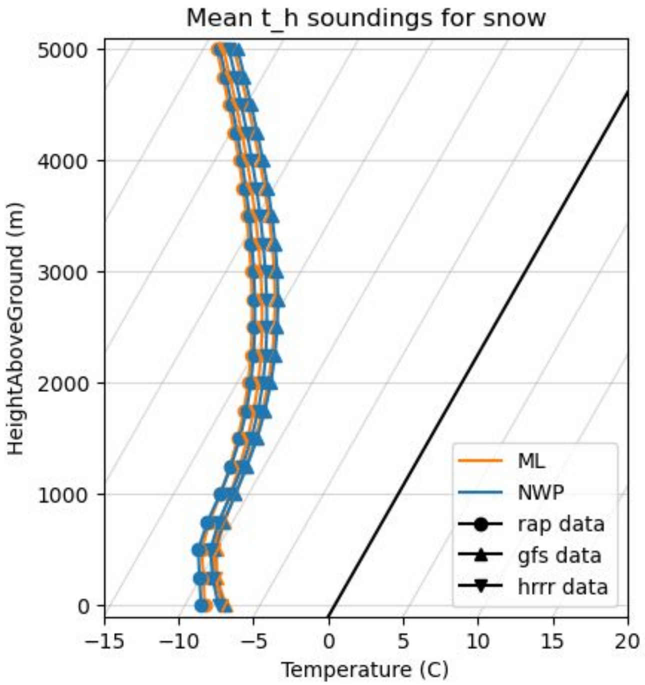
Evaluation: Composite Soundings



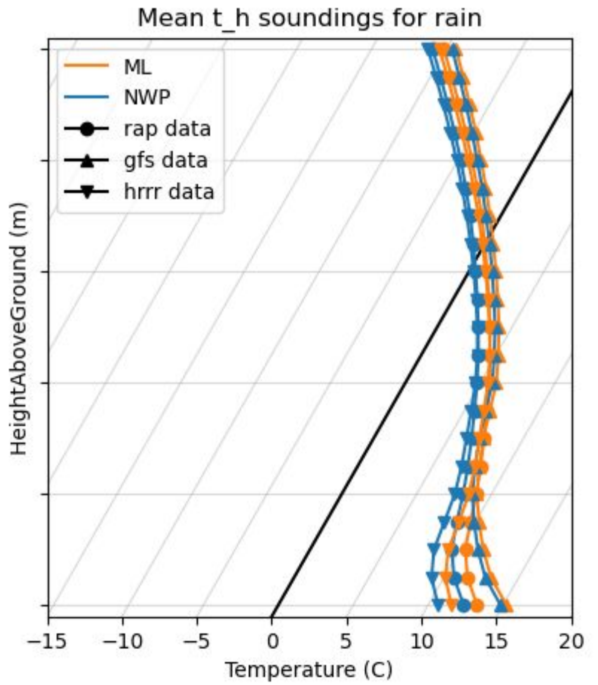
	rap	gfs	hrrr
ML frac_abv_0	0.97	0.96	0.96
NWP frac_abv_0	0.79	0.99	0.78
ML num_obs	2.1E+06	7.2E+04	3.7E+07
NWP num_obs	3.5E+06	6.1E+04	6.2E+07



	rap	gfs	hrrr
ML frac_abv_0	0.71	0.66	0.72
NWP frac_abv_0	0.89	0.94	0.89
ML num_obs	3.0E+06	1.3E+05	5.6E+07
NWP num_obs	8.7E+05	7.0E+04	1.6E+07



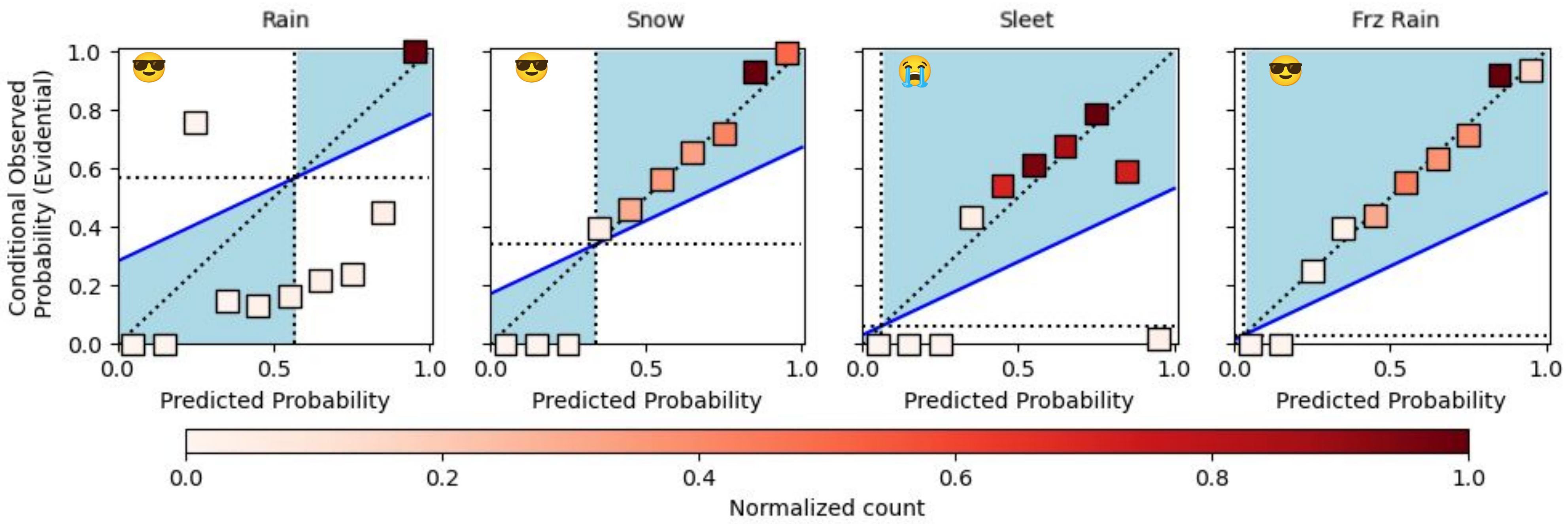
	rap	gfs	hrrr
ML frac_abv_0	0.10	0.11	0.11
NWP frac_abv_0	0.08	0.10	0.10
ML num_obs	5.2E+07	1.7E+06	6.7E+08
NWP num_obs	5.2E+07	1.7E+06	6.7E+08



	rap	gfs	hrrr
ML frac_abv_0	1.00	1.00	1.00
NWP frac_abv_0	1.00	1.00	1.00
ML num_obs	3.3E+07	1.7E+06	4.2E+08
NWP num_obs	3.6E+07	1.8E+06	4.6E+08

- Means are taken over 3TB of data
- Required significant engineering

Evaluation: Calibration

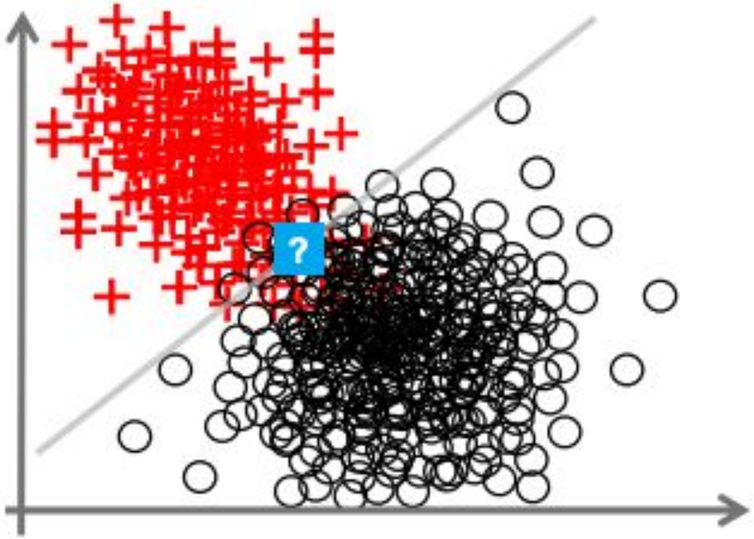


Ideal calibration curve: x=y line.

Why? ex. If model predicts label rain with probability p then true label should be rain p fraction of the time over examples the model predicts rain

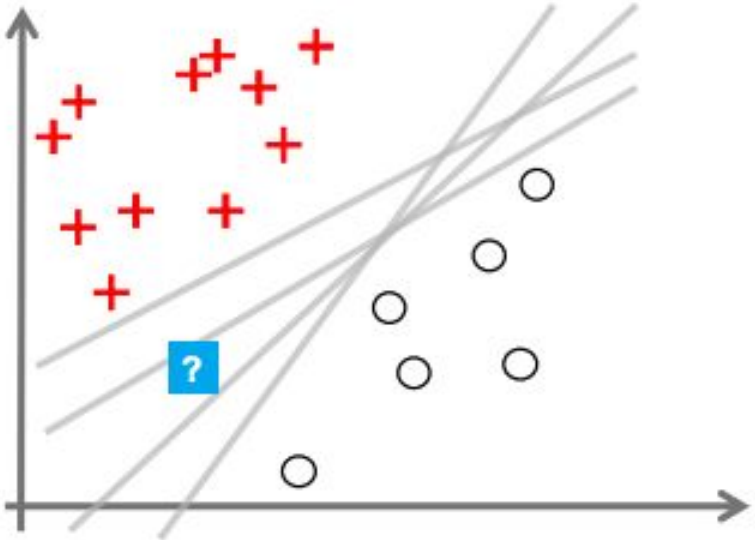
*figure by John Schreck of NCAR MILES group

Quick Aside: Uncertainty Quantification



Aleatoric Uncertainty

- irreducible
- inherent in the data

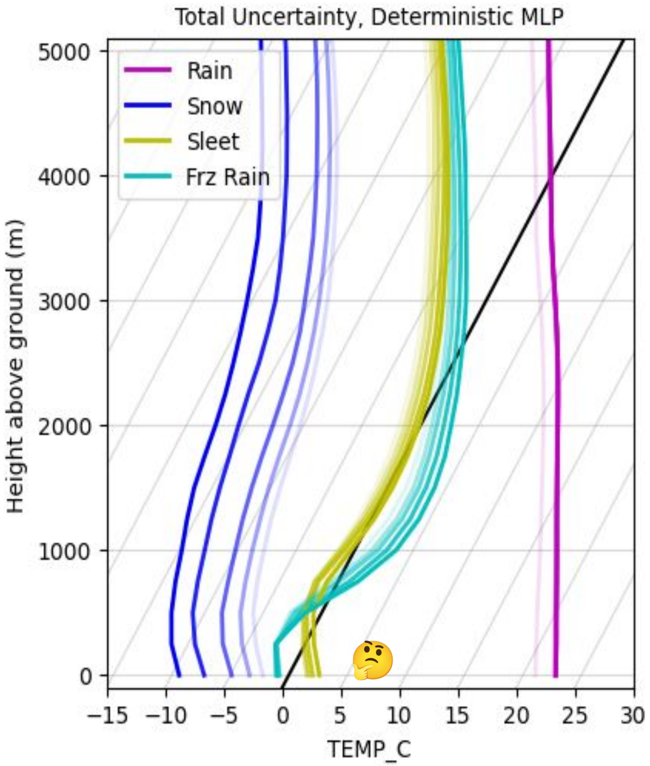


Epistemic Uncertainty

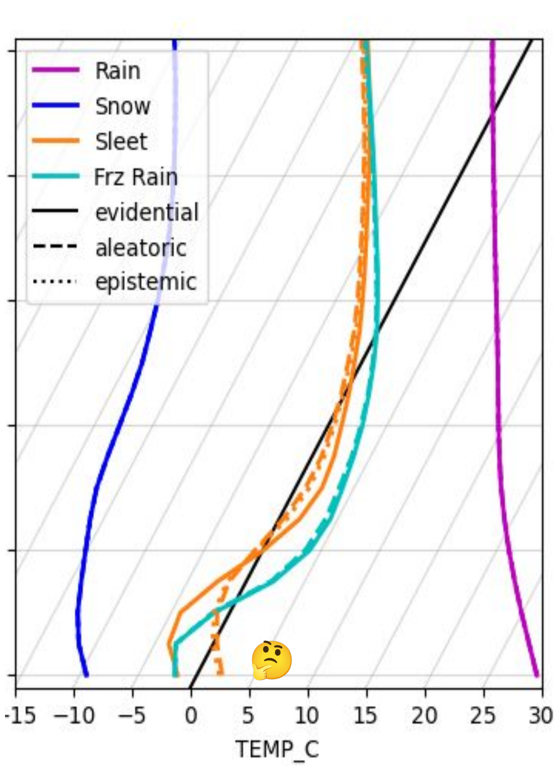
- reducible with more data, better modeling etc

Evidential Models can estimate uncertainty:
Sensoy, M., Kaplan, L., & Kandemir, M. (2018). Evidential deep learning to quantify classification uncertainty. Advances in neural information processing systems, 31.

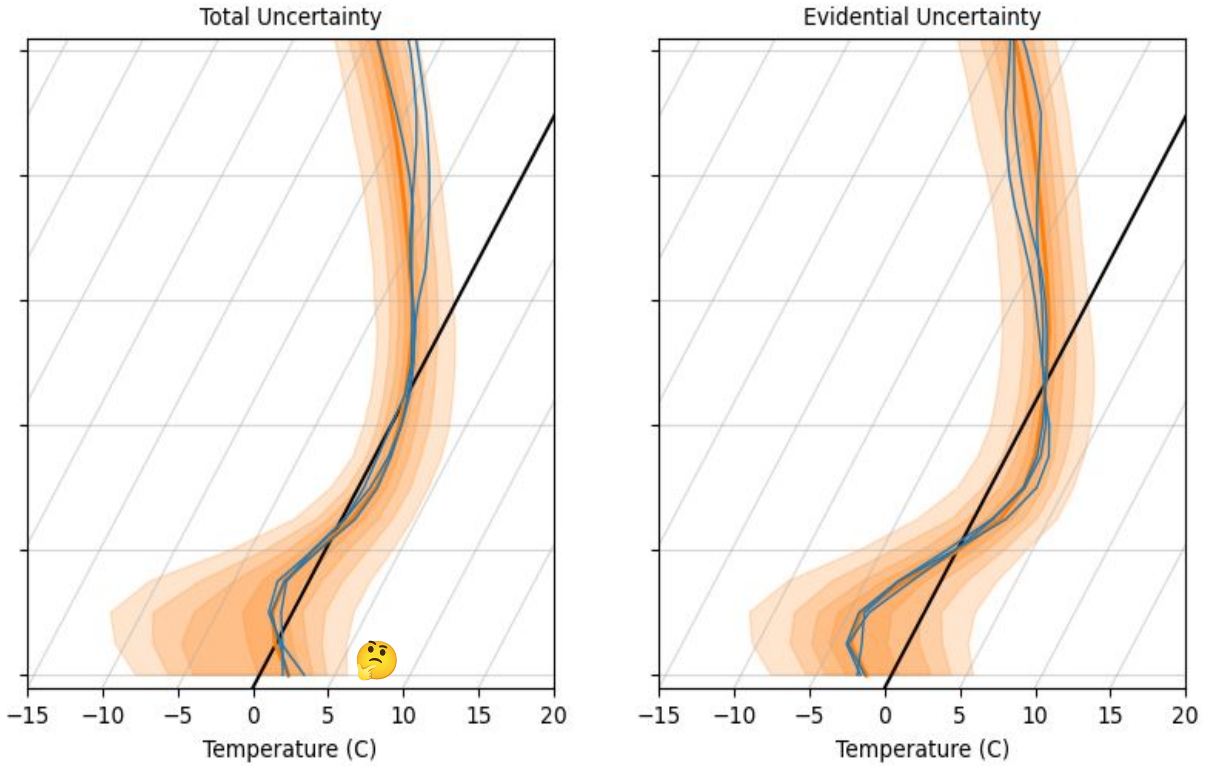
Evaluation: binned by uncertainty



MLP with Monte Carlo Dropout



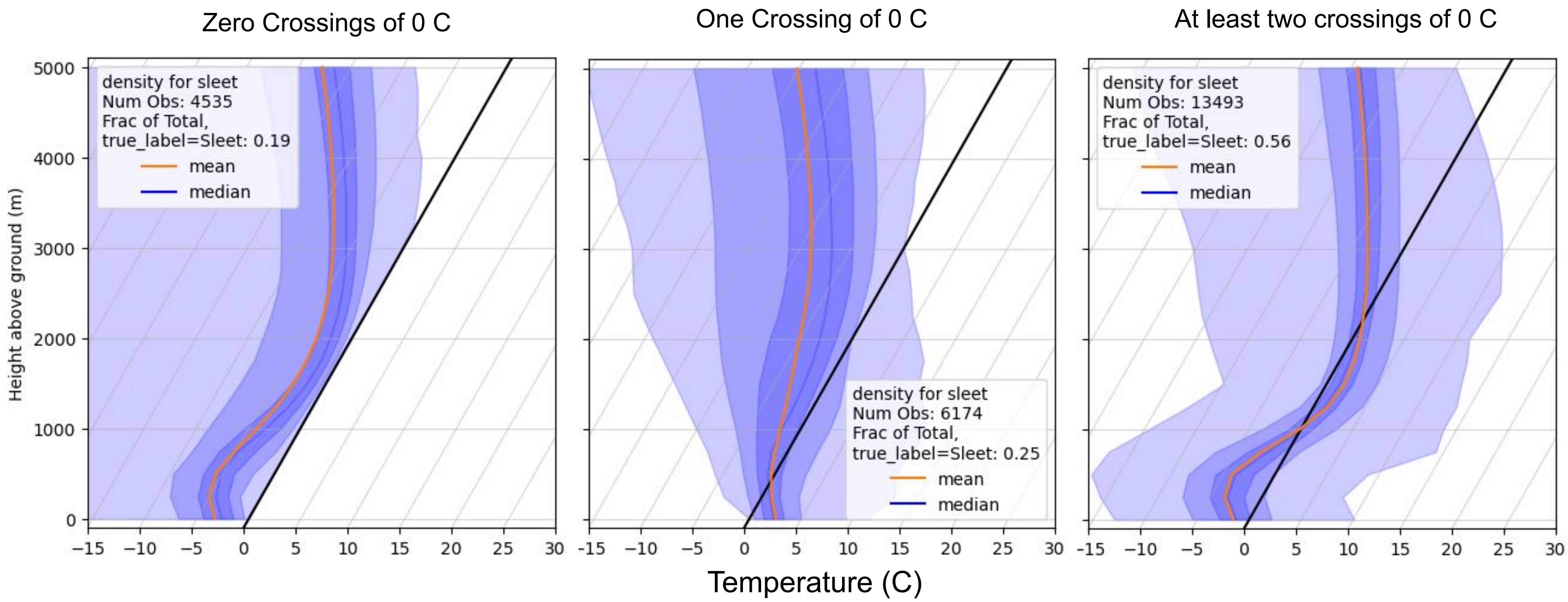
Evidential Model



Evidential Model, Sleet

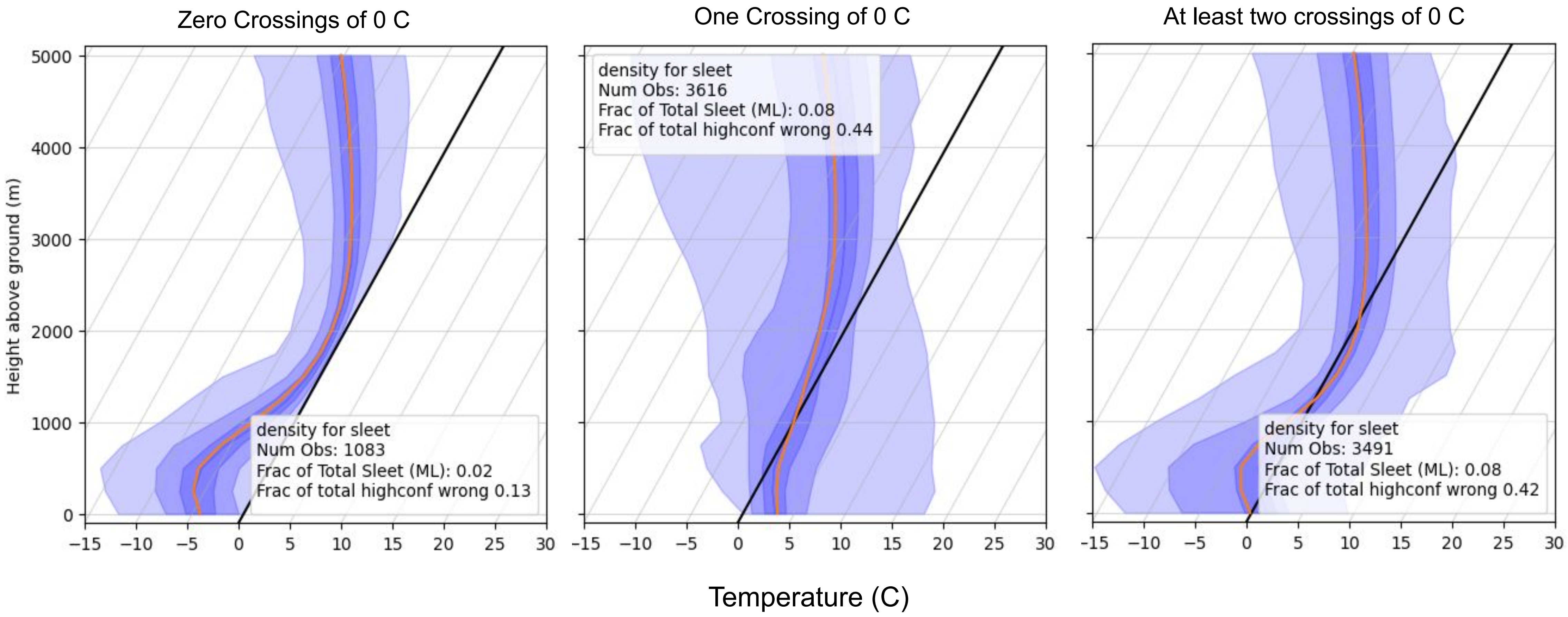
Root cause: Data Quality

- “ground truth” labels are from crowdsourced observations
- some quality control done, but not enough:



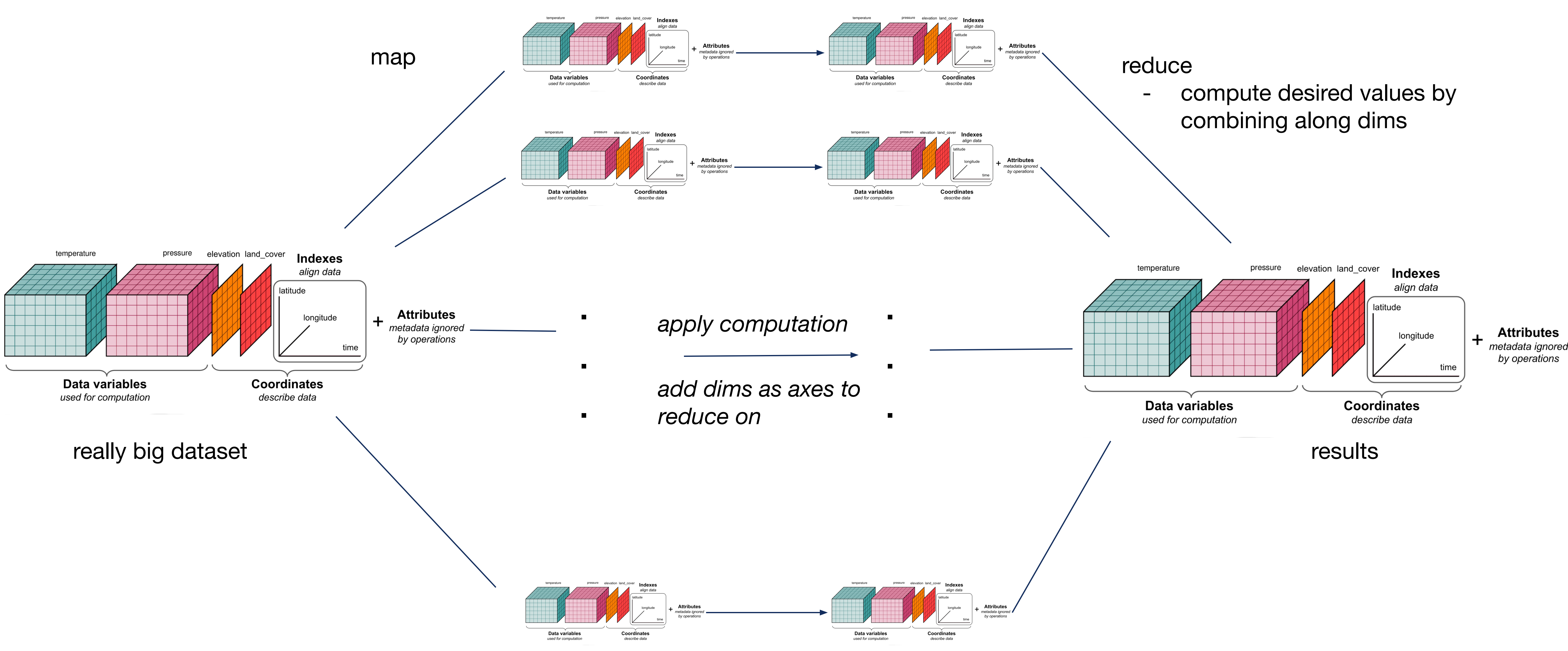
Root cause: Data Quality

- Soundings for high confidence and “wrong” ML predictions



End of evaluation section

Alternative approach to large Dask computations on large Xarray datasets



Pros/Cons

Pros

- less finicky than Dask which is very sensitive to chunking

- usually exists good approximations to expensive single-threaded computations e.g. histograms for quantile computation. Single threaded version: sort

Cons

- more user overhead
- not every function can be map-reduced
  - non parallelizable functions will be slow in dask also

Conclusion

Issues

- Which true labels for sleet are actually sleet?
- Evidential model has uncertainty blow-up

Future work

→ Further detailed investigation into convective precip. soundings

→ Use other NWPs for soundings

→ Improve loss function of evidential model

→ Hierarchical model to predict precip. type

→ Incorporate physics into model

Statistics

lines of code committed: 3396

file type	lines of code
.py	1484
.ipynb	1912

	Total	Per Business Day
CPU use	3400 core-hours	72 core-hours
RAM use	18594 gb-hours	395 gb-hours

Acknowledgements

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- John Schreck

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