Knowledge-Informed Approaches for Airborne Magnetic Anomaly Navigation

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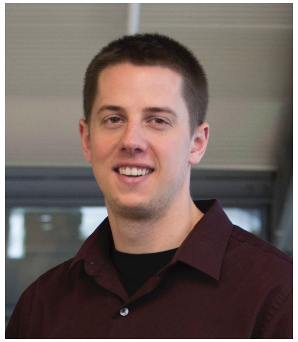
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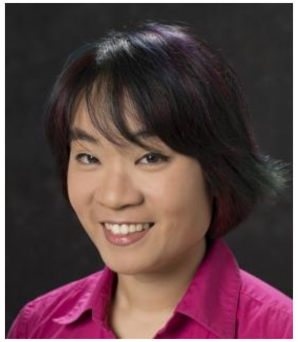
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MagNav.jl contains a full suite of open-source MagNav-related tools written in Julia

https://github.com/MIT-AI-Accelerator/MagNav.jl

- Import or simulate flight path & INS data
  - Open-source data via artifacts
- Map functions
  - KNN fill-in, upward & downward continuation, …
- Aeromagnetic compensation models
  - Tolles-Lawson, online, NN-based
- Navigation algorithms
  - EKF, MPF, neural EKF

julia

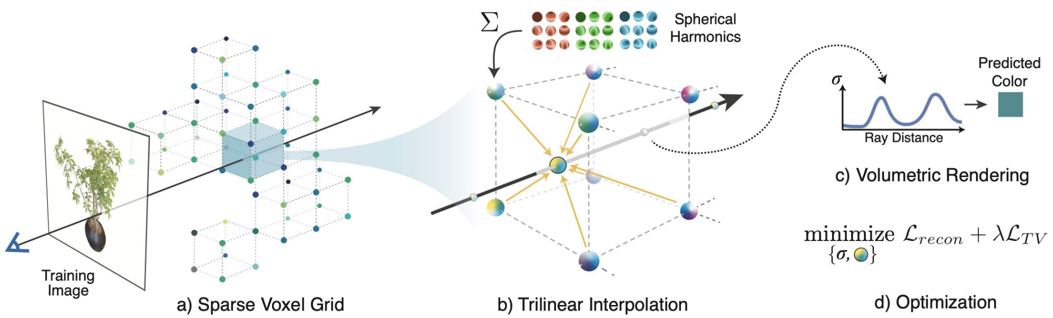
(obligatory plug)

https://julialang.org/

Mainstream examples of knowledge-informed AI

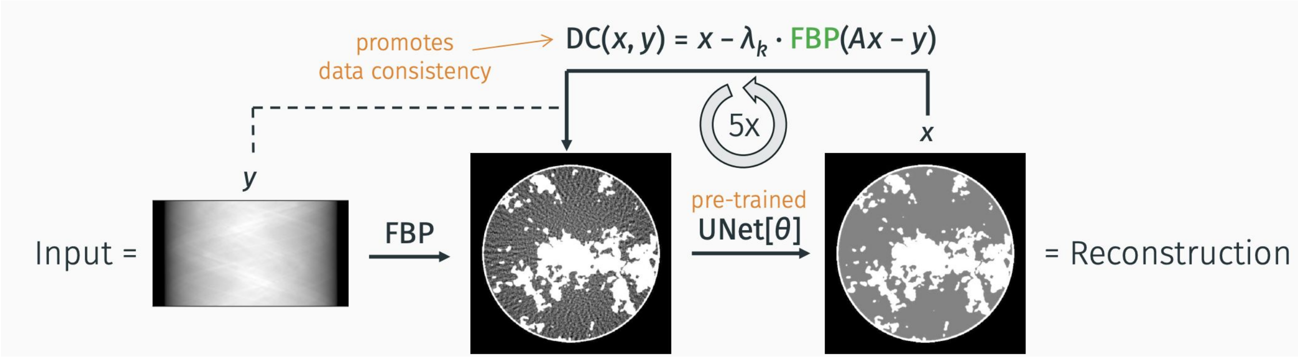
Knowledge-informed AI: knowledge-guided/constrained deep learning approaches promise appealing performance gains (accuracy, generalizability, explainability, efficient use of resources)

- Neural Radiance Fields (NeRF) or Plenoxels[1], in computer vision



trained in minutes, real-time inference

- Inverse problems for medical imaging using "data consistency"[2]

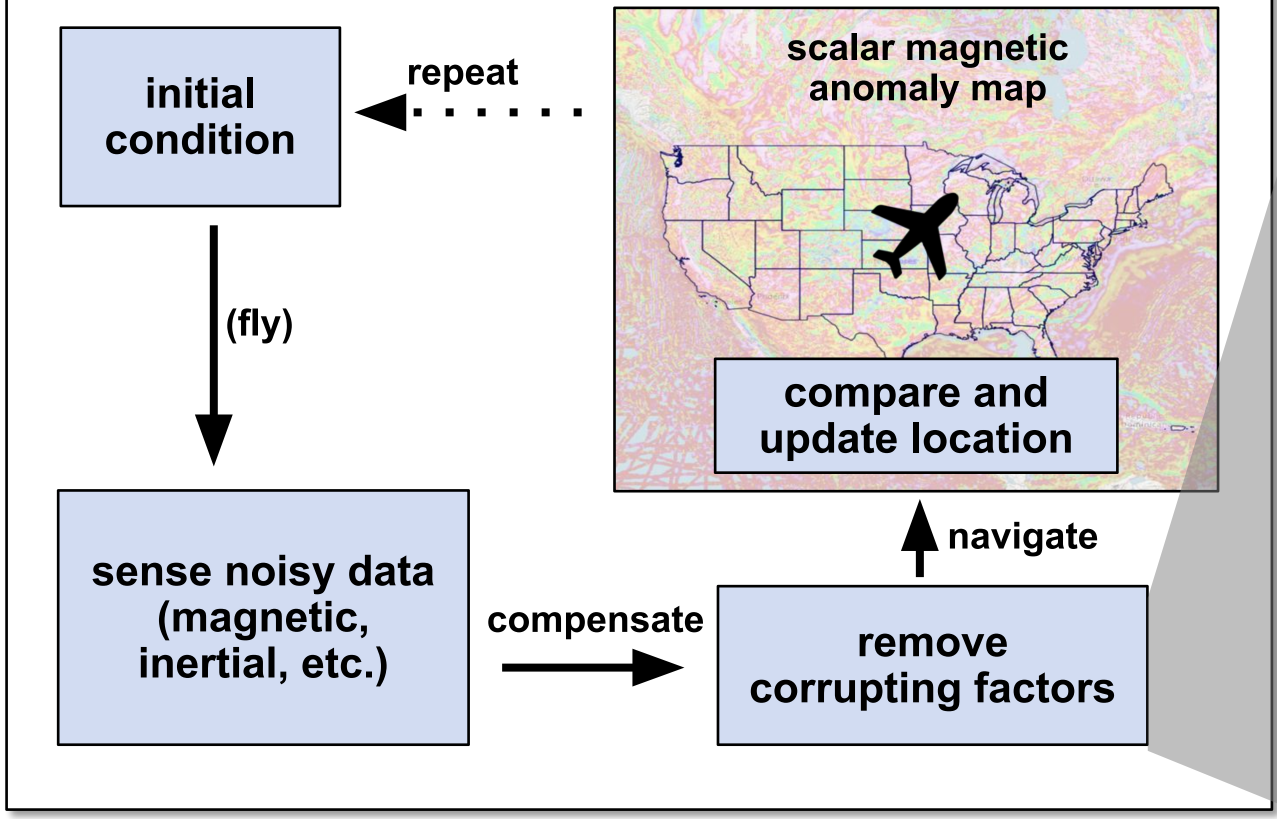


won AAPM data challenge by an order of magnitude

[1]A. *et al.*, "Plenoxels: Radiance Fields without Neural Networks," *arXiv*, 2021, doi:10.48550/arXiv.2112.05131.
[2]M. Genzel, I. Gühring, J. Macdonald, & M. März, "Near-Exact Recovery for Tomographic Inverse Problems via Deep Learning," *arXiv*, 2022, doi:10.48550/arxiv.2206.07050.

Knowledge-informed AI for magnetic navigation

Positioning in GPS-denied environments via Real-Time Magnetic Navigation Process



Conventional approach toward extracting Earth's magnetic field from total magnetic field fails with noisy sensor readings → AI augmentation

Magnetic Signal Sources

- Core field ~50,000 nT
- Temporal variations ~10 nT
- Anomaly field ~100 nT
- **Platform effects**

  → geo-survey <10 nT

  → fighter jet >1000 nT

Observable fields

(Tolles-Lawson model*)

- Permanent
- Induced
- Eddy

Transient fields

- Comms
- Radar
- Lights, etc.

Knowledge-informed AI approaches leverage the conventional model while learning from data

*Since 1950s, the Tolles-Lawson model has provided a means for removing a corrupting aircraft magnetic field from a total magnetic field measurement

Knowledge-informed approaches for MagNav

Use TL to extend expensive flight data for rare sensor actuations

knowledge-informed dataset

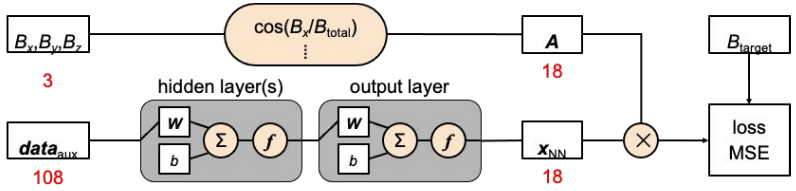
neural network

$$\widetilde{B_T}(x+\delta_x) = B_T(x) + \delta_x B_T'(x) + O(\delta_x^2) \approx B_T(x) + \delta_x(B'_{P,TL} + B'_{Earth})$$

Modify vanilla NN architecture to embed TL terms

knowledge-informed architecture

knowledge in architecture and/or weights of network



Incorporate the TL terms into the loss function and back-propagate through TL-based architecture

informed learning algorithm

loss function modified according to knowledge

Compute $\mathcal{L}(B_{Earth}, |\vec{B}_T - \vec{B}_p|)$ with

$$\vec{B}_p = \vec{B}_{Perm} + \vec{B}_{Induced} + \vec{B}_{Eddy} + \vec{B}_{Res}$$

Impose TL-based bounds during inference

learned-model consistency check

neural network

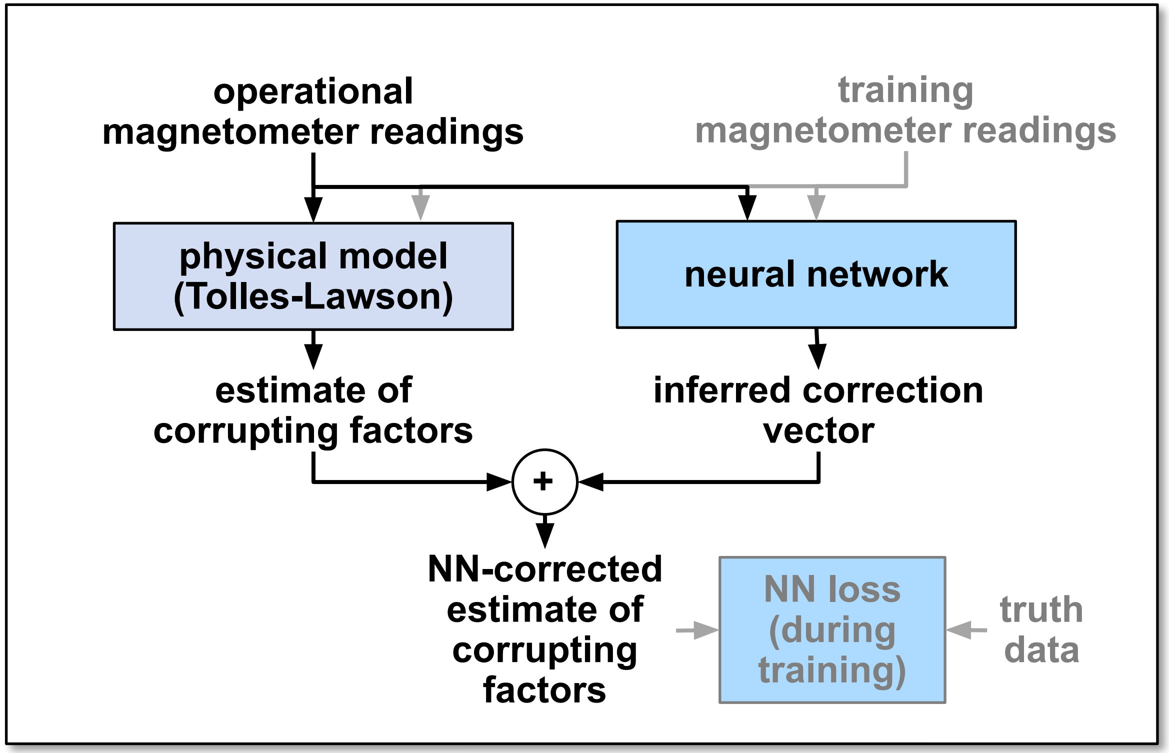
$$B_T - \max(B_{P,TL}) \le B_{Earth} \le B_T + \max(B_{P,TL})$$

Developed each approach to compare knowledge integration across different integration points

TL: Tolles-Lawson

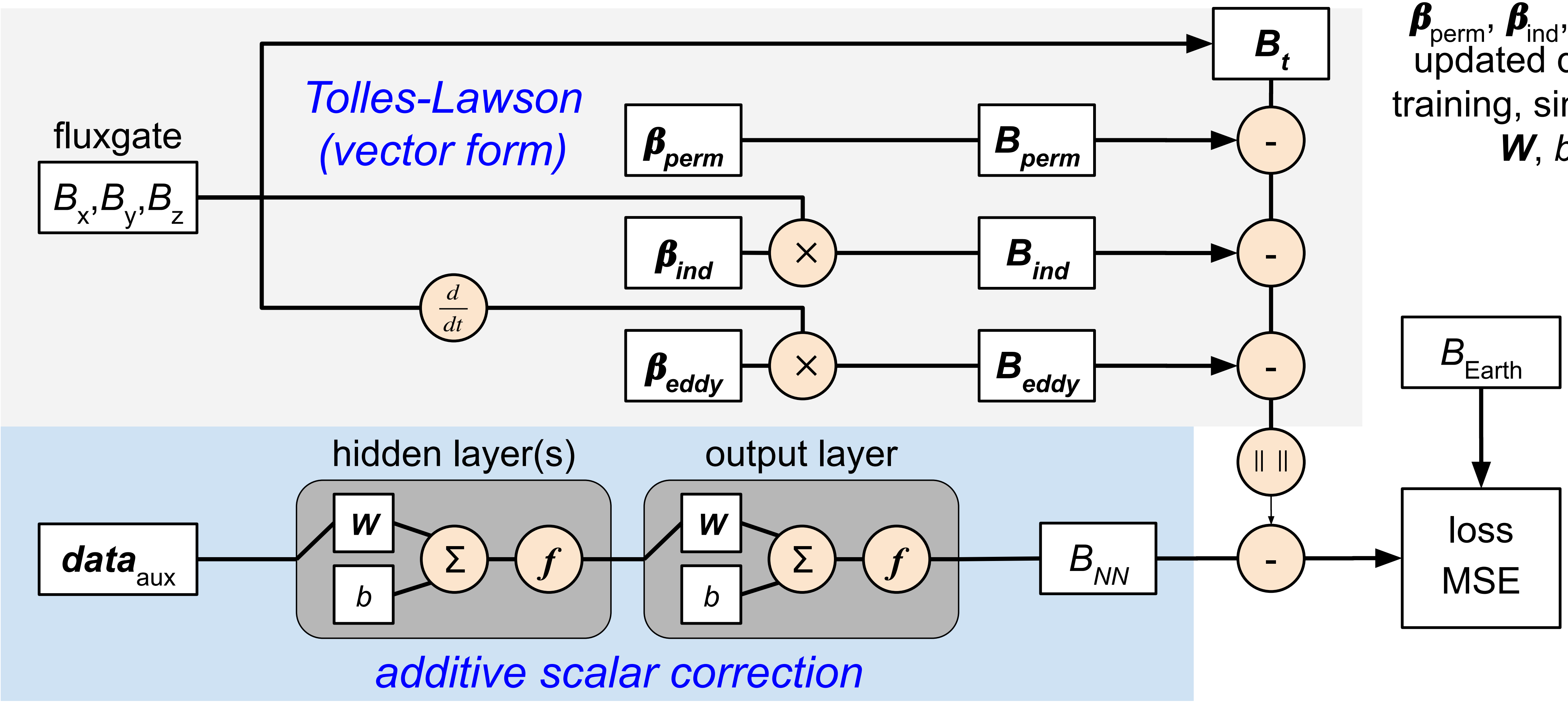
Knowledge-informed architecture

- Approach: embed Tolles-Lawson model directly into the architecture
  - Julia enables auto-differentiation over arbitrary parameters (not just NN weights)
- Hypothesis: building on linear model should enable rapid learning (using less training flight time) and explainability
- Experimental setup:
  - Randomly select 20 of 25 flight lines from the training data
  - Test on 7 navigable, held-out flight lines (200 training runs per architecture)



NN-assisted Tolles-Lawson model plays to the strengths of both compensation approaches

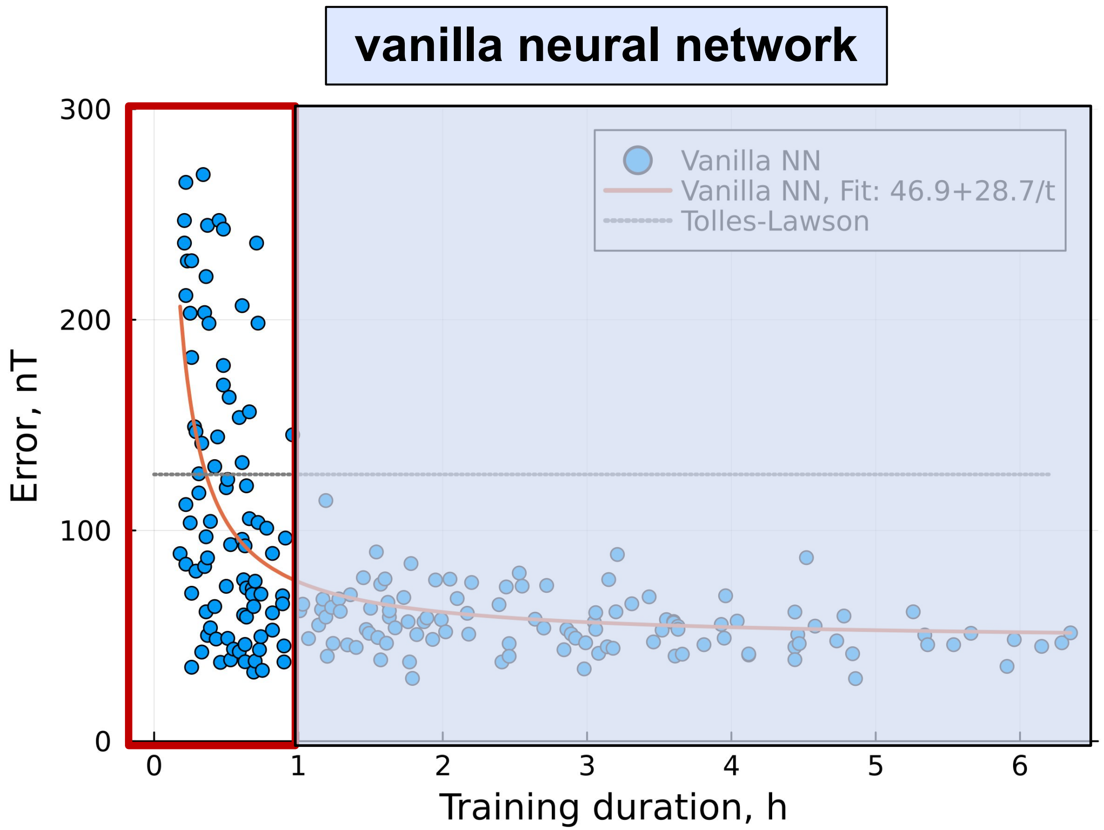
Knowledge-informed architecture learns both linear & nonlinear compensation portions

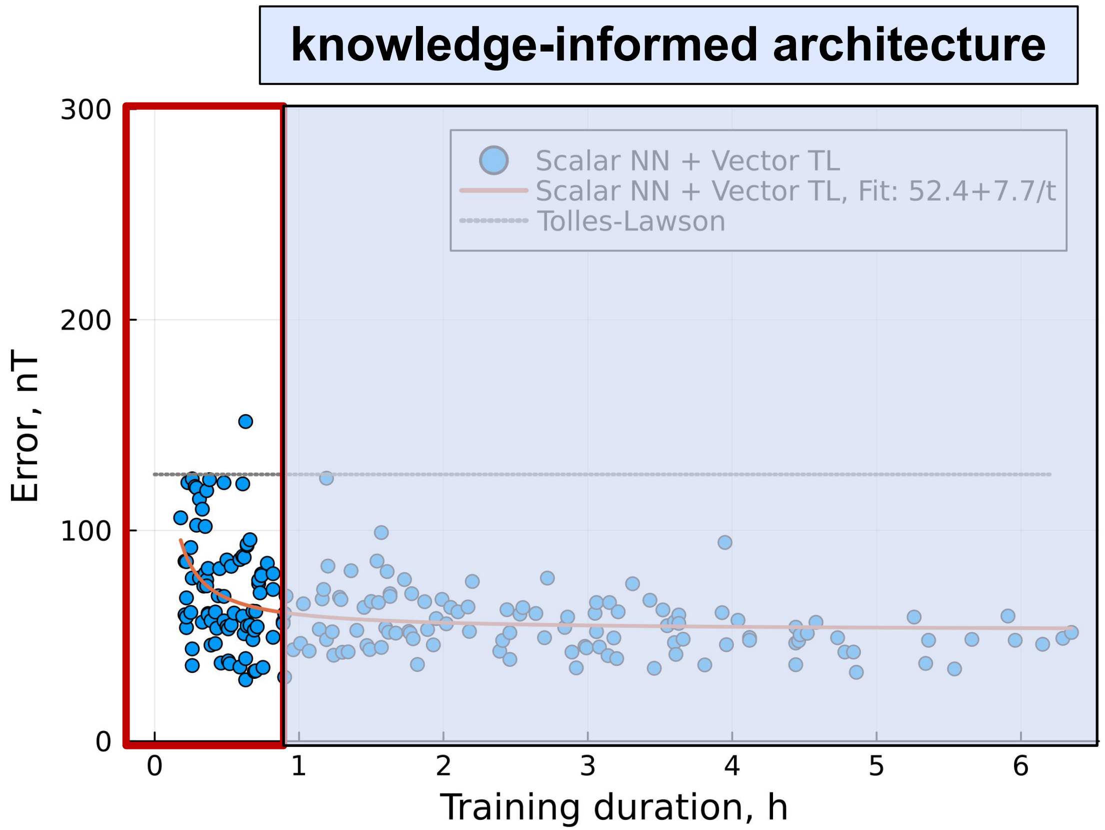


$\boldsymbol{\beta}_{perm}$, $\boldsymbol{\beta}_{ind}$, $\boldsymbol{\beta}_{eddy}$, updated during training, similar to $\boldsymbol{W}$, b

$$\left|\left|\vec{B}_{\text{Earth}}\right|\right| = \left|\left|\vec{B}_t - \vec{B}_p\right|\right| = \left|\left|\vec{B}_t - (\vec{B}_{\text{perm}} + \vec{B}_{\text{ind}} + \vec{B}_{\text{eddy}} + \vec{B}_{NN})\right|\right| \approx \left|\left|\vec{B}_t - \begin{bmatrix}\beta_{p,x}\\ \beta_{p,y}\\ \beta_{p,z}\end{bmatrix} - \begin{bmatrix}\beta_{i,xx} & \beta_{i,xy} & \beta_{i,xz}\\ \beta_{i,xy} & \beta_{i,yy} & \beta_{i,yz}\\ \beta_{i,xz} & \beta_{i,yz} & \beta_{i,zz}\end{bmatrix}\vec{B}_t - \begin{bmatrix}\beta_{e,xx} & \beta_{e,xy} & \beta_{e,xz}\\ \beta_{e,yx} & \beta_{e,yy} & \beta_{e,yz}\\ \beta_{e,zx} & \beta_{e,zy} & \beta_{e,zz}\end{bmatrix}\vec{B}_t' - \vec{B}_{NN}\right|\right|$$

Knowledge-informed architecture results

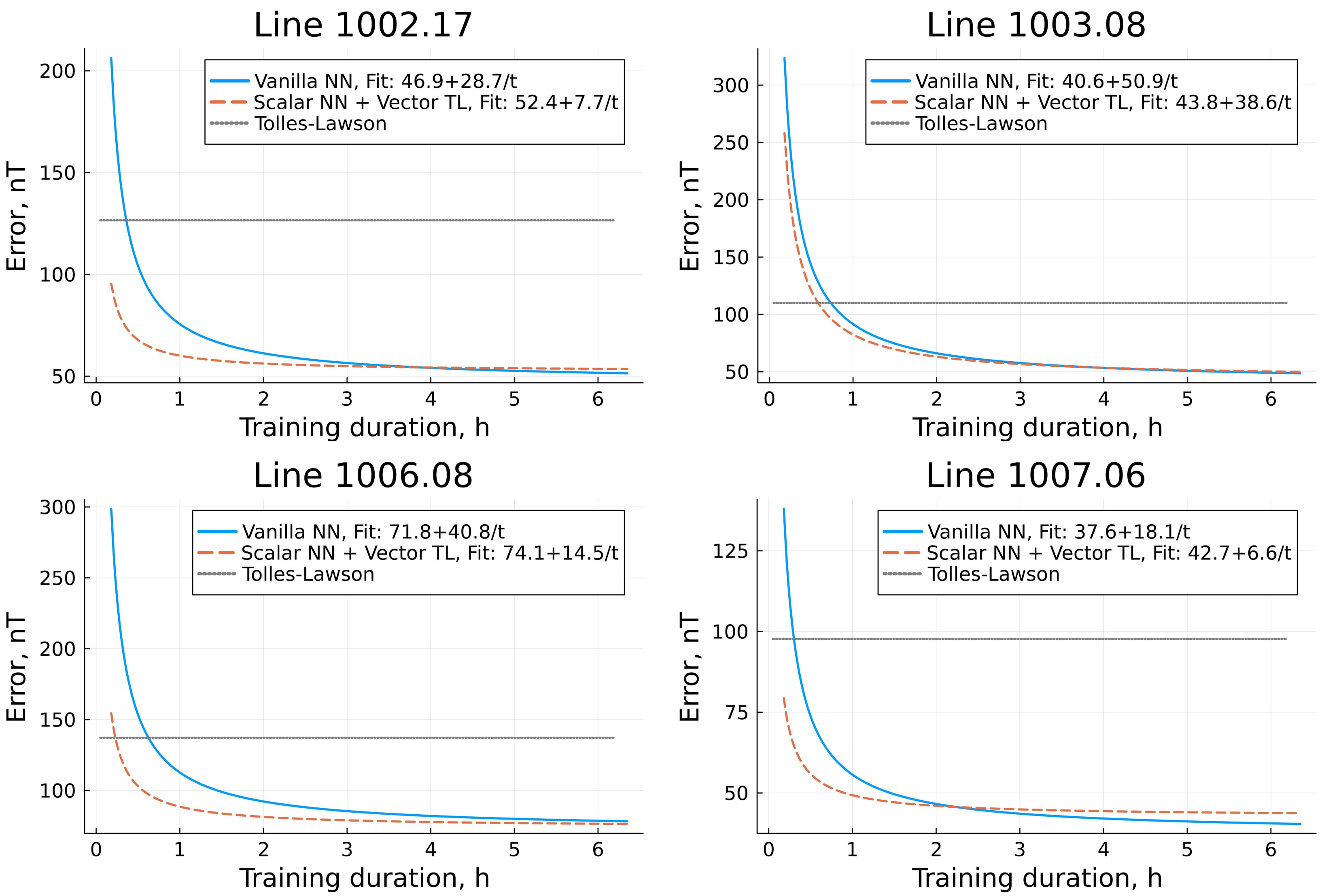




In 200 train/test experiments, the KI architectures typically are more accurate with less data

Knowledge-informed architecture result trendlines

- In general, this informed architecture achieves lower compensation error for <1 hr of flight data
  - Operational relevance: model could be calibrated in as little as 30 min of data-collect
- Gains diminish as more training data is made available (>2 hr)



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→ neural network →

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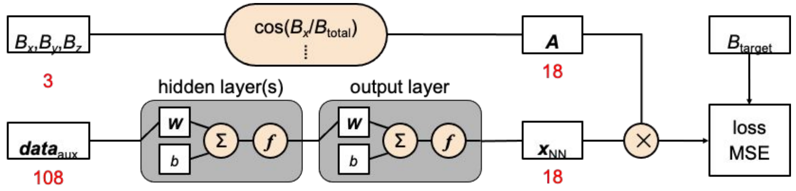

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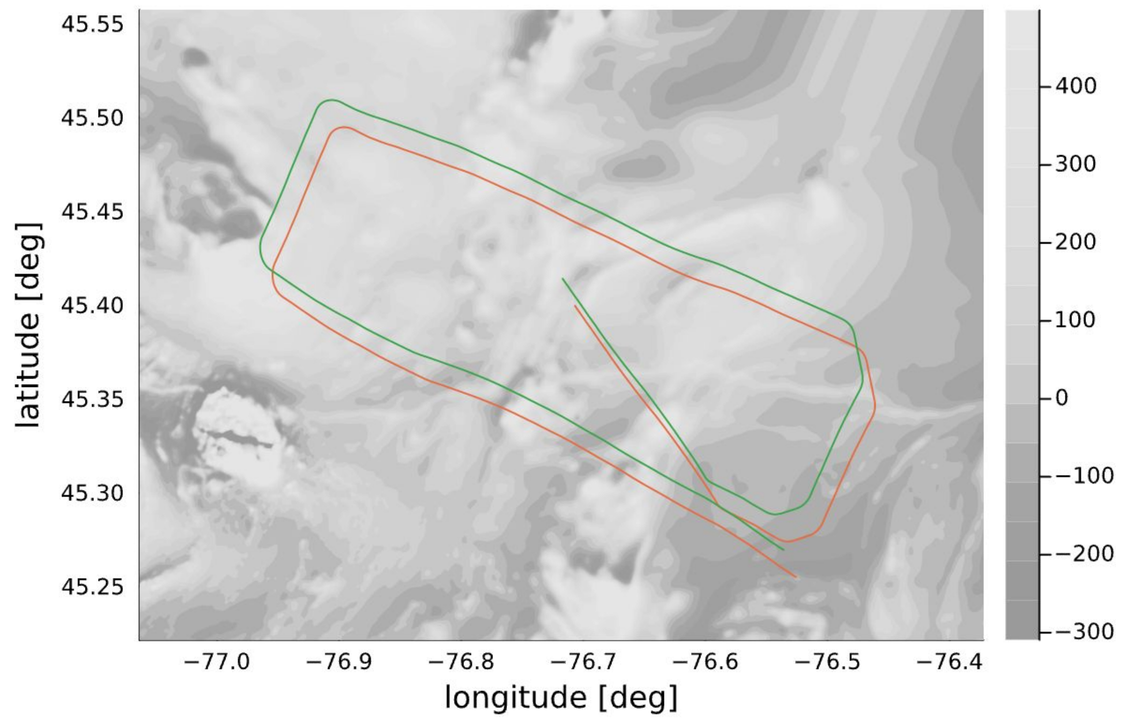
Developed each approach to compare knowledge integration across different integration points

TL: Tolles-Lawson

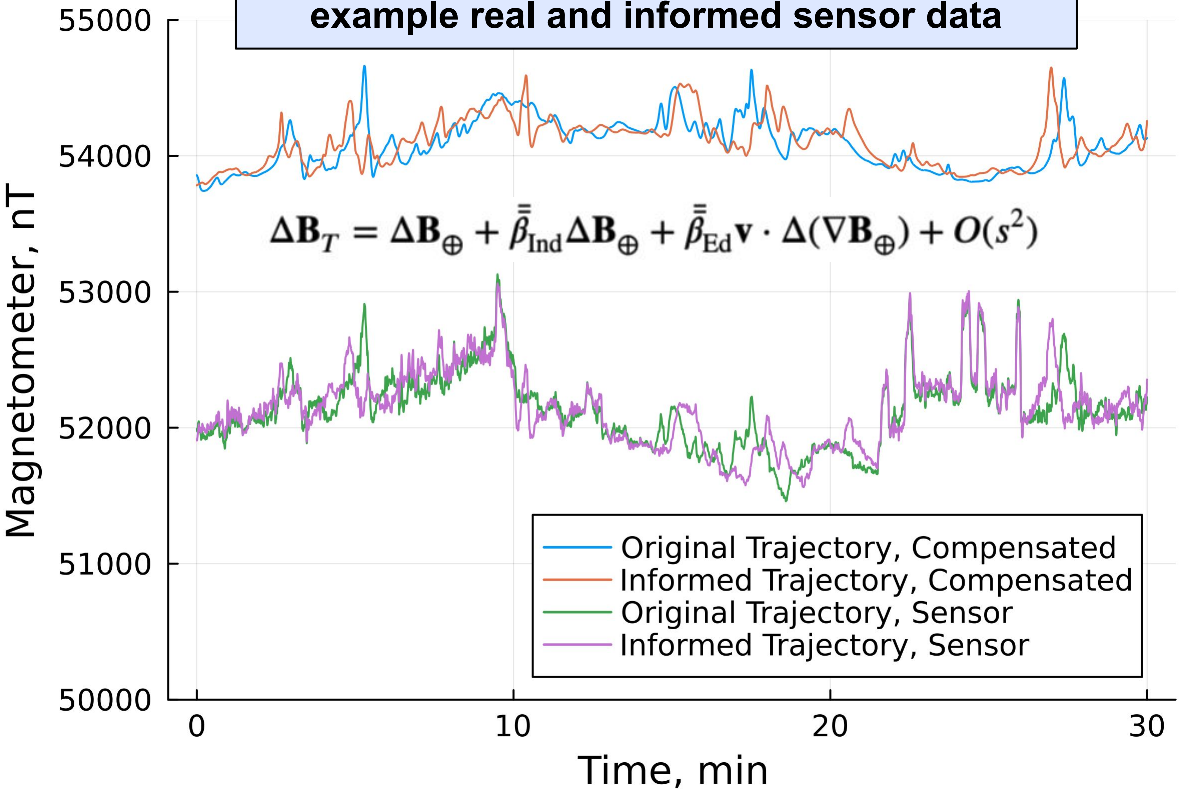
Knowledge-informed dataset

- Flight data is expensive to collect, and there are no obvious symmetries to exploit
- Hypothesis: the Tolles-Lawson model can enable data augmentation on a similar flight trajectory
- Experimental setup: select navigable training lines and consistently recompute the compensated and uncompensated sensor data using a Taylor expansion for data augmentation

example real and displaced flight trajectory



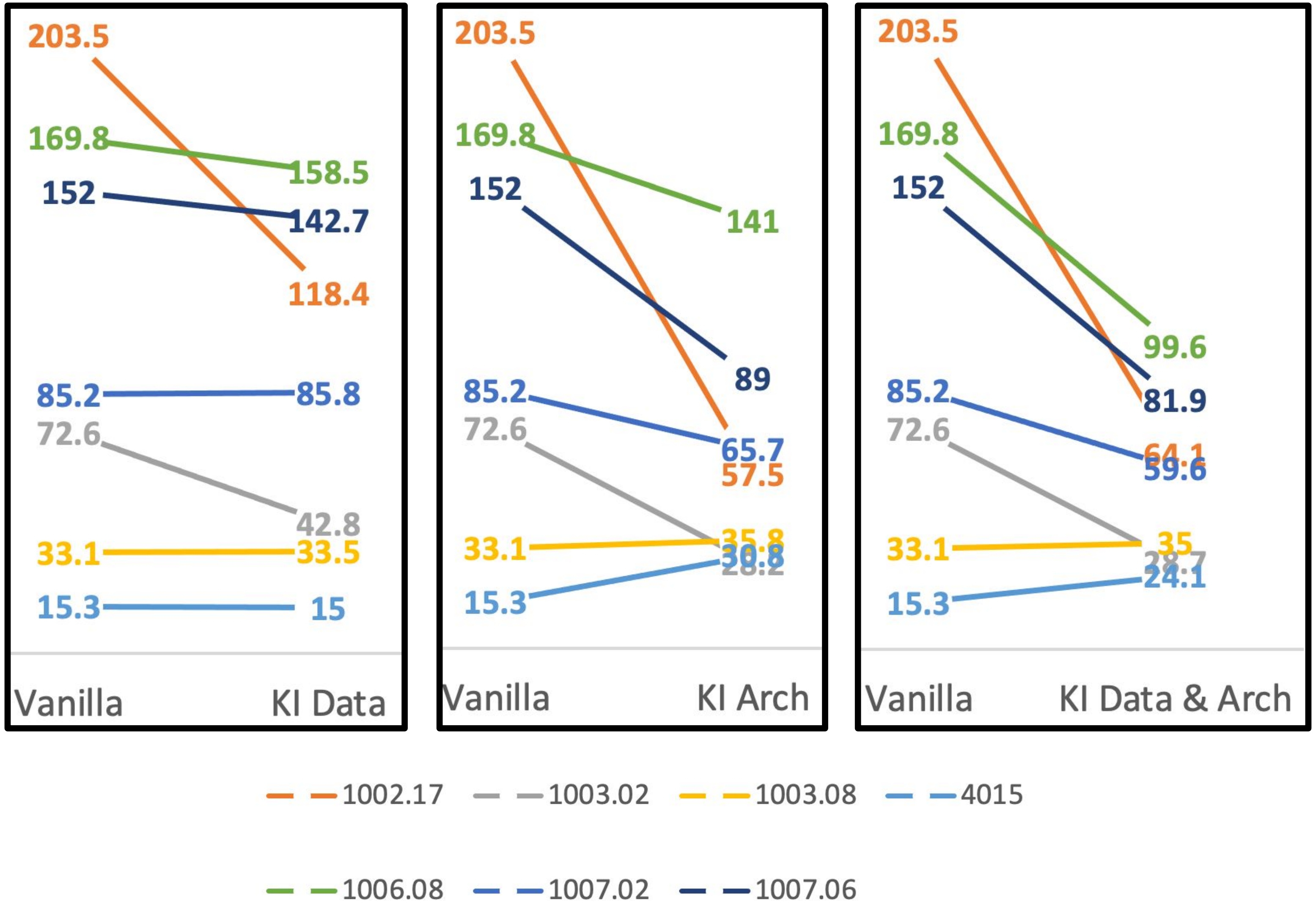
example real and informed sensor data



$$\Delta \mathbf{B}_T = \Delta \mathbf{B}_\oplus + \bar{\bar{\beta}}_{\text{Ind}} \Delta \mathbf{B}_\oplus + \bar{\bar{\beta}}_{\text{Ed}} \mathbf{v} \cdot \Delta(\nabla \mathbf{B}_\oplus) + O(s^2)$$

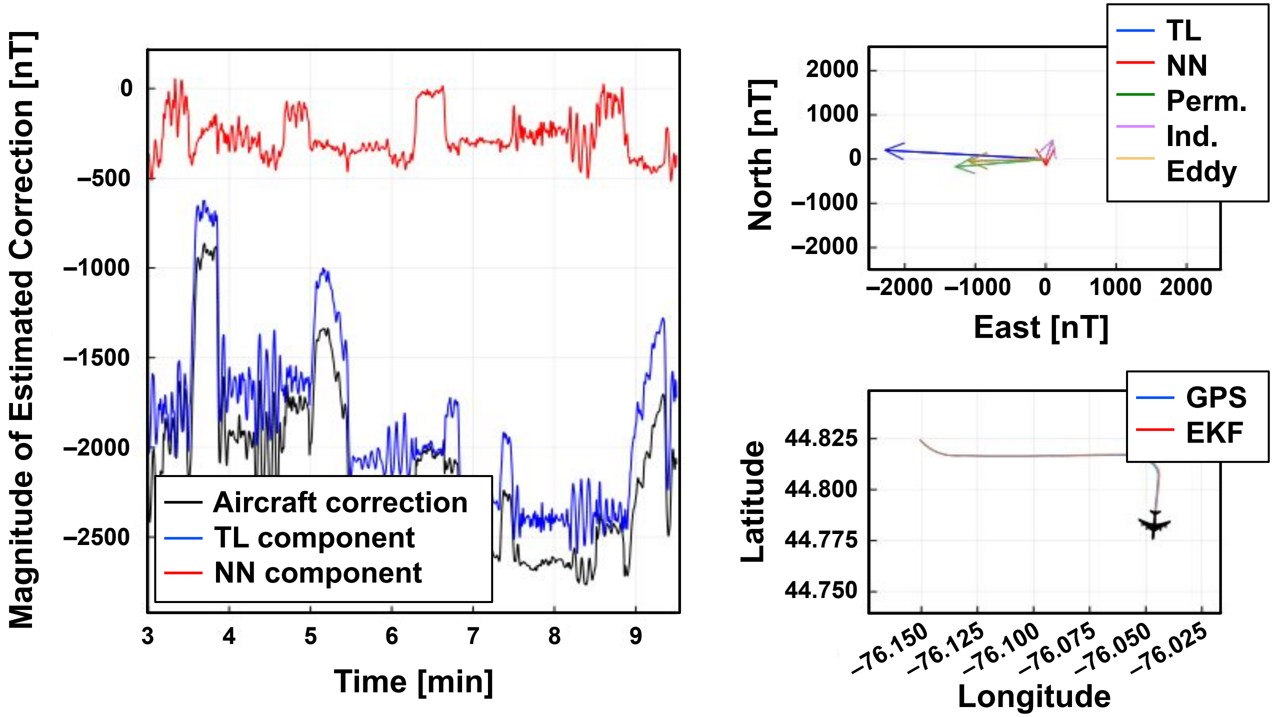
KI dataset + KI architectures results

- For very limited training data (<30 min), KI dataset can help
  - 2 of 7 flight lines show marked improvement, 2 others some improvement, none for the remaining 3
  - In other results, using over 1 hr of data (not shown), KI dataset had little to no effect
- KI architectures on this limited data did pretty well
- KI dataset + KI architecture generally has best performance



Additional outcomes and tech transfer

Pseudo Real-time Error Correction Performance



Model	Magnetic Field Error [nT]	Navigation Error [m]
Tolles-Lawson*	134	149
Vanilla NN	67	116
Tolles-Lawson + NN	55	74

- Approach allows for same-flight calibration and compensation
- KI architectures also require less training energy with early stopping
- Explainability (example at left) helps in understanding which components are contributing to the aircraft signal

KI approaches have been integrated into MagNav.jl[1,2] and publicly released

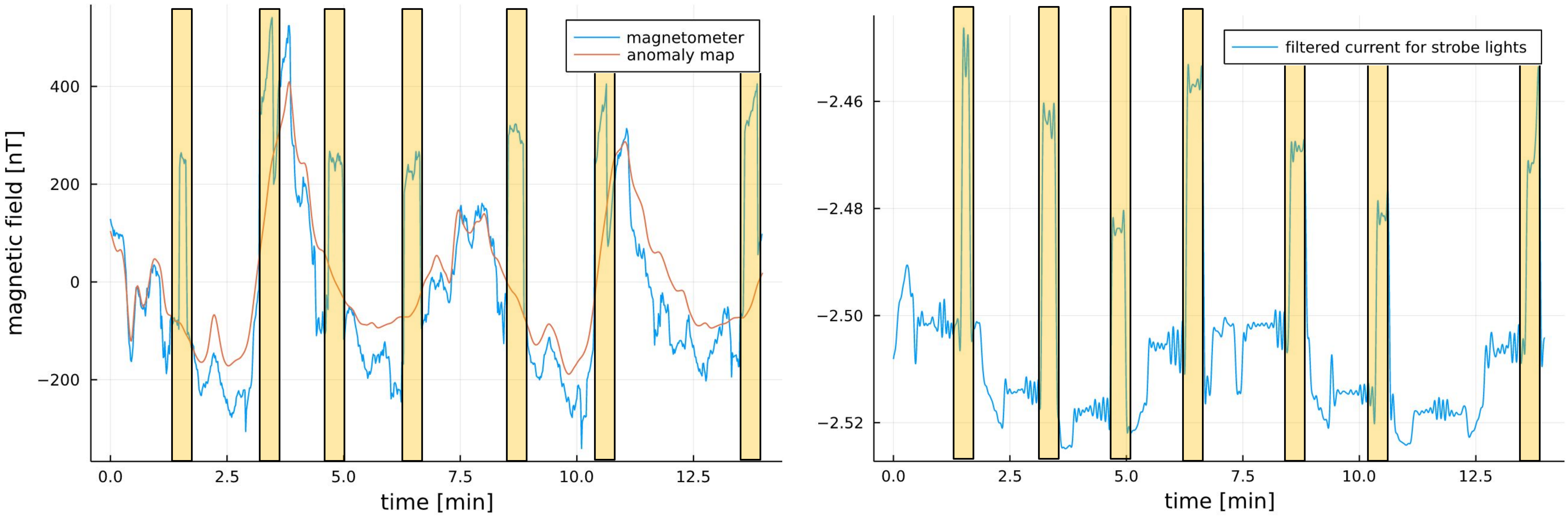
[1]https://github.com/MIT-AI-Accelerator/MagNav.jl
[2]https://magnav.mit.edu/

TL: Tolles-Lawson
NN: neural network

GPS: Global Positioning System
EKF: extended Kalman filter

Knowledge-informed learning approaches for airborne magnetic anomaly navigation, paper in preparation for Journal of the Institute of Navigation (ION)

Example transients from strobe lights

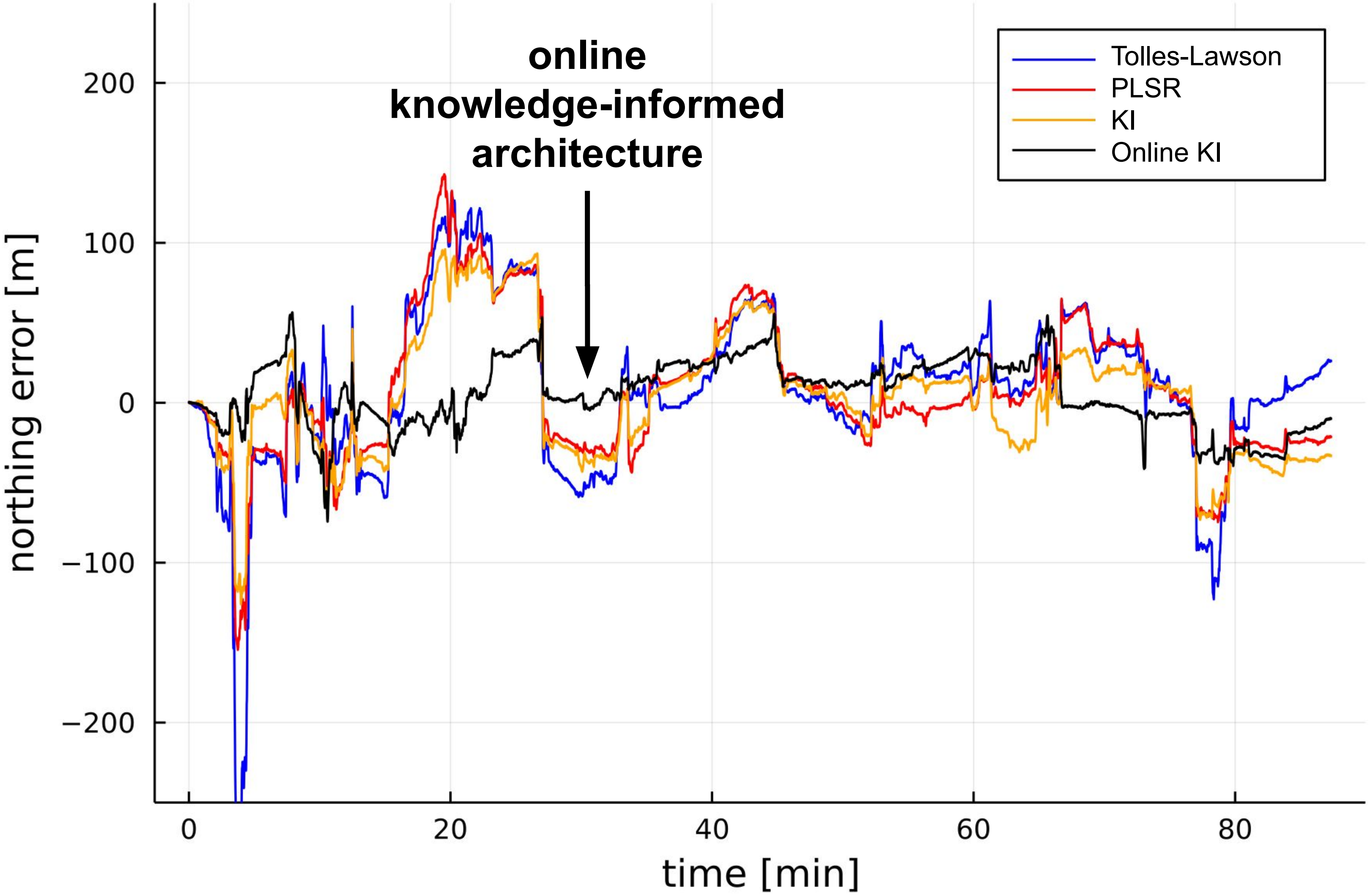


7 “excursions” are difficult to predict

Online knowledge-informed architecture shows potential for improved navigation performance

$$\hat{\boldsymbol{x}} = \begin{bmatrix} \delta \boldsymbol{p} \\ \delta \boldsymbol{v} \\ \boldsymbol{\epsilon} \\ \boldsymbol{a} \\ \boldsymbol{g} \\ \delta h_a \\ \delta \hat{a} \\ S \\ \boldsymbol{w}_{\mathrm{NN}} \end{bmatrix}$$

neural network weights



For reference: INS drifts ~400 m

Current & future data collections & collaborations

- SGL flight data collection #2: public data release (late 2023)
- SGL flight data collection #3: NV diamond magnetometer & tensor gradiometer
- USAF transition: integrating with flight hardware & real-time demonstration
- Collaborations with AFIT, AFRL, & industry
- Open challenge problem: https://magnav.mit.edu/