2026 JULY 19–22 VANCOUVER, BC
JOINT AAPM | COMP MEETING

Self-Supervised Learning for Radiotherapy CT-CBCT Patient-Plan Anomaly Detection

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Background

- External beam radiotherapy requires highly accurate patient positioning to ensure the prescribed dose is delivered to the target volume while minimizing the dose to the surrounding healthy organs
- Setup differences between the simCT and CBCT are often corrected before the radiotherapy fraction is delivered; however, anomalies that are missed by the human reviewers can pose a threat to patient safety
- Clinically significant anomalies are rare and varied; unsupervised anomaly detection learns the normal correspondence between the simCT and the CBCT to detect deviations from this normal relationship without requiring training on predefined anomaly types
- **Our work proposes an automated deep learning anomaly-detection algorithm to flag anomalous CT-CBCT registrations for expert review**

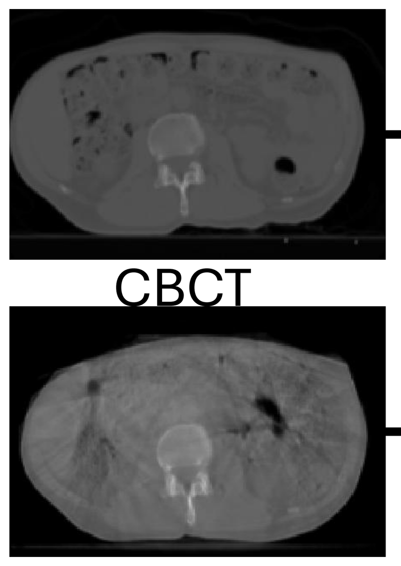
Methods

- Two Siamese networks were separately trained, fine-tuning a SWIN-UNETR backbone, where both networks used different loss functions
- Three clinically motivated anomaly types were evaluated across different treatment regions: wrong-patient CT-CBCT mismatches, 20-mm translational shifts, and off-by-one vertebral misalignments
- Model performance was evaluated comparing anomaly scores for normal registration with each anomaly type

A. Data Collection and Preprocessing

SimCT

CBCT



Preprocessing

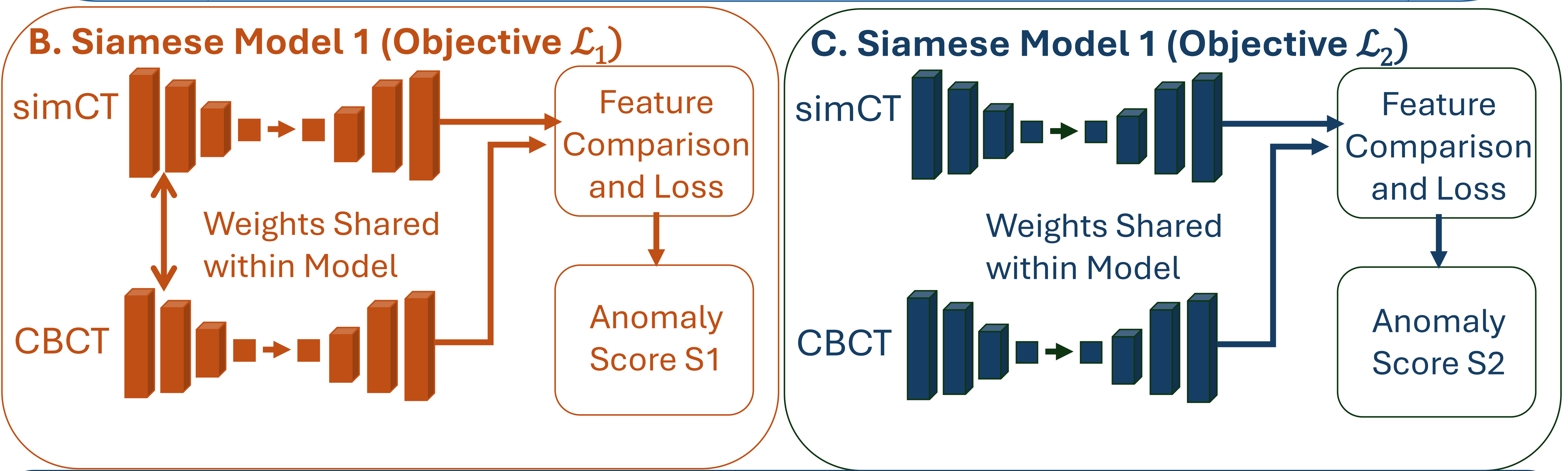
1. Registration
2. Resampling
3. Resizing
4. Normalization
5. Centering

Normal Dataset

- 5,750 Training Fractions
- 1,280 Validation Fractions
- 1,500 Test (Normal) Fractions

Swin-UNETR Pretrained Model

Same Pretrained Weights – Independently Finetuned



D. Held Out Evaluation

1500 Normal Fractions Unseen During Training

Simulated Anomaly Types (Testing Only)

1. Simulated Wrong Patient Mismatch
2. 20-mm shifts in x,y,z direction
3. Off-by-one vertebral misalignments

Evaluate Models

1. Score S1
2. Score S2
3. Compare S1/S2

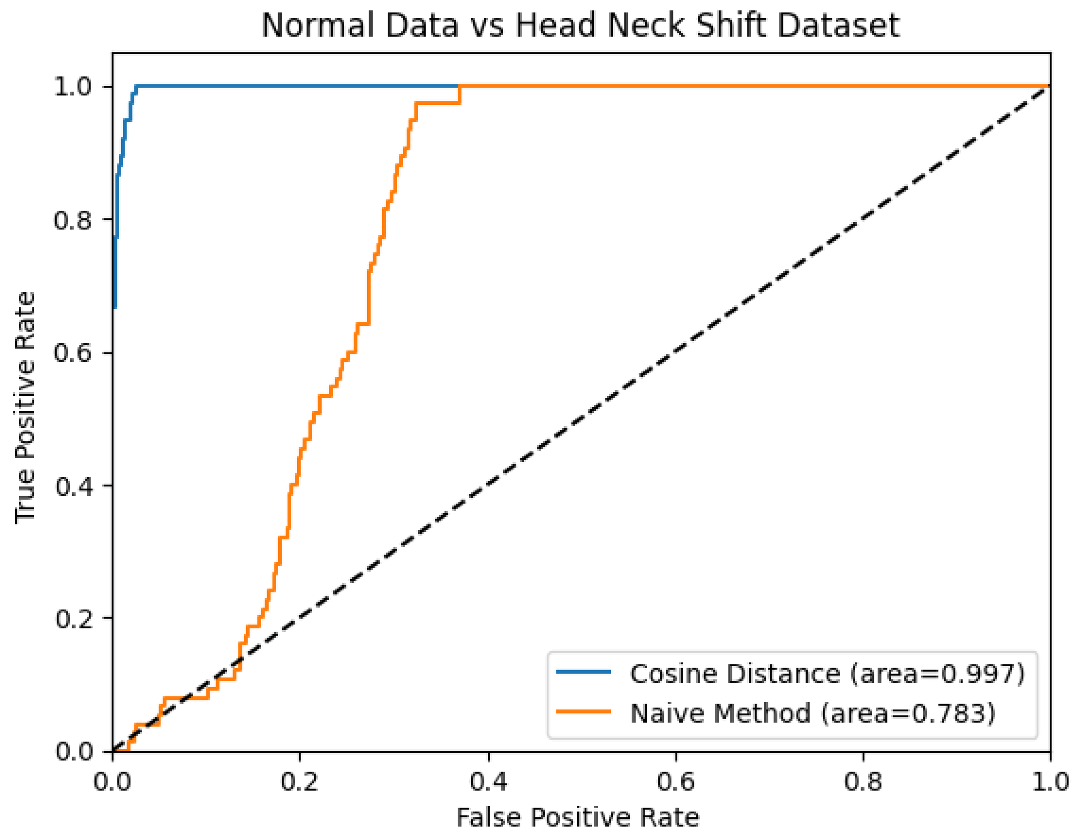
$$\mathcal{L}_1 = -\frac{1}{2BM}\sum_{d\in\{CT\to CBCT, CBCT\to CT\}}\sum_{b=1}^{B}\sum_{i\in A_b} log\left(\frac{\exp(sim(\mathbf{z}_{b,i}^{d_a},\mathbf{z}_{b,i}^{d_t})/\tau}{\sum_{j=1}^{N} exp\left(sim\left(\mathbf{z}_{b,i}^{d_a},\mathbf{z}_{b,i}^{d_t}\right)/\tau\right)}\right)$$

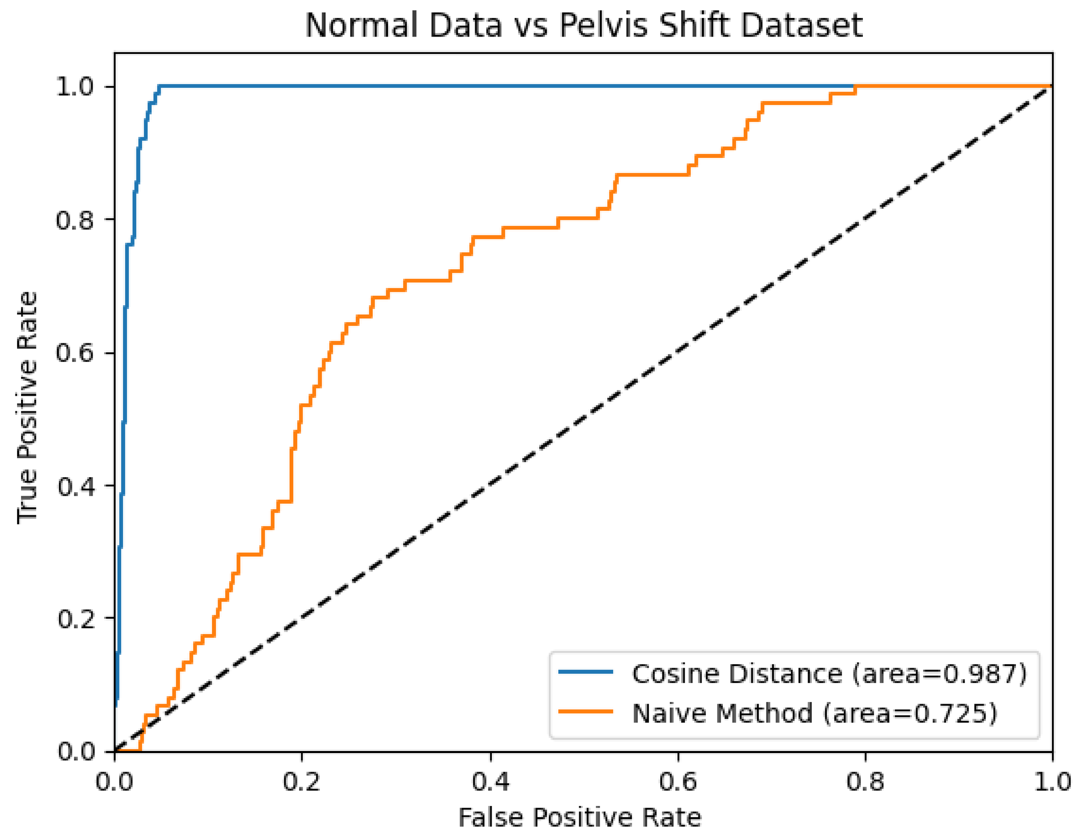
B: batch size
N: # overlapping patches
A_b: M random sampled anchors for b
$\mathbf{z}_{b,i}^{m}$: normalized embedding at patch i

$$\mathcal{L}_2 = \lambda_{pos} max\left(0, m_{pos} - S_{align}\right)^2 + \lambda_{near}\max\left(0, S_{near} + m_{near} - S_{align}\right) + \lambda_{far}\max\left(0, S_{far} + m_{far} - S_{align}\right)$$

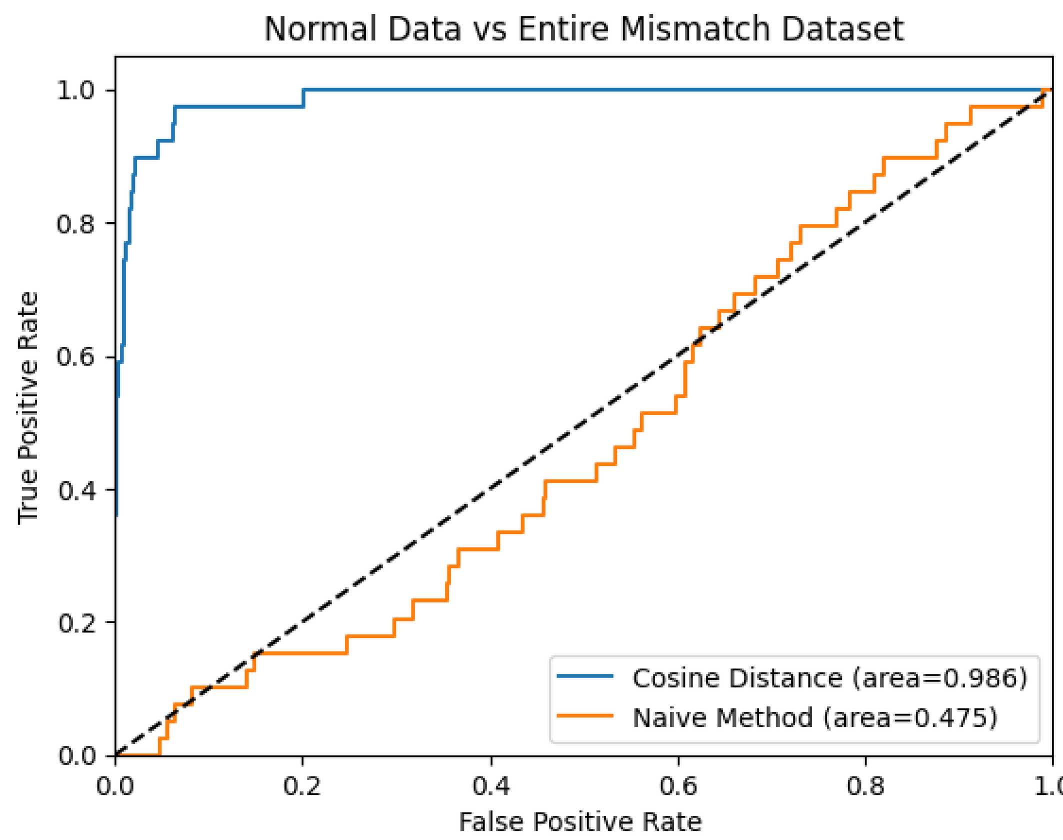
S_{align}: cosine similarity between aligned patches S_{near}: max cos sim between n nearest neighbors
S_{far}: max cos sim between any other patch m_{pos}, m_{near}, m_{far}: hyperparameters to enforce spatial awareness

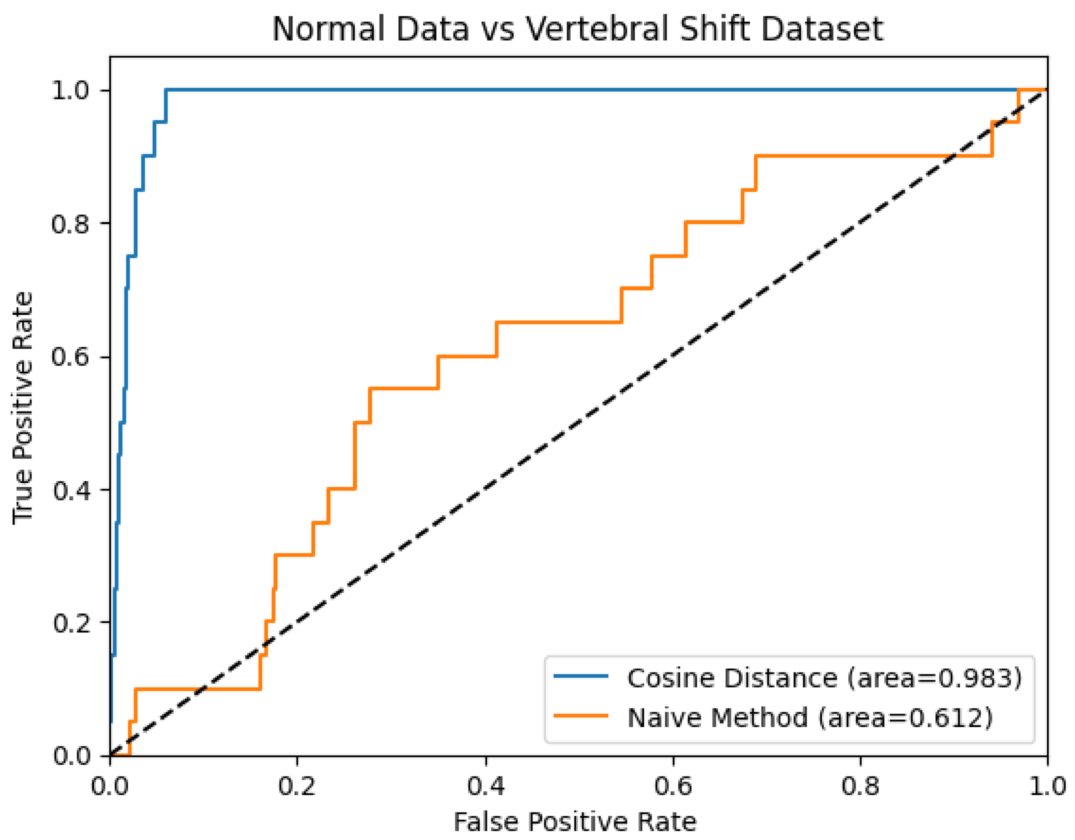
Best AUC Results: Model 1





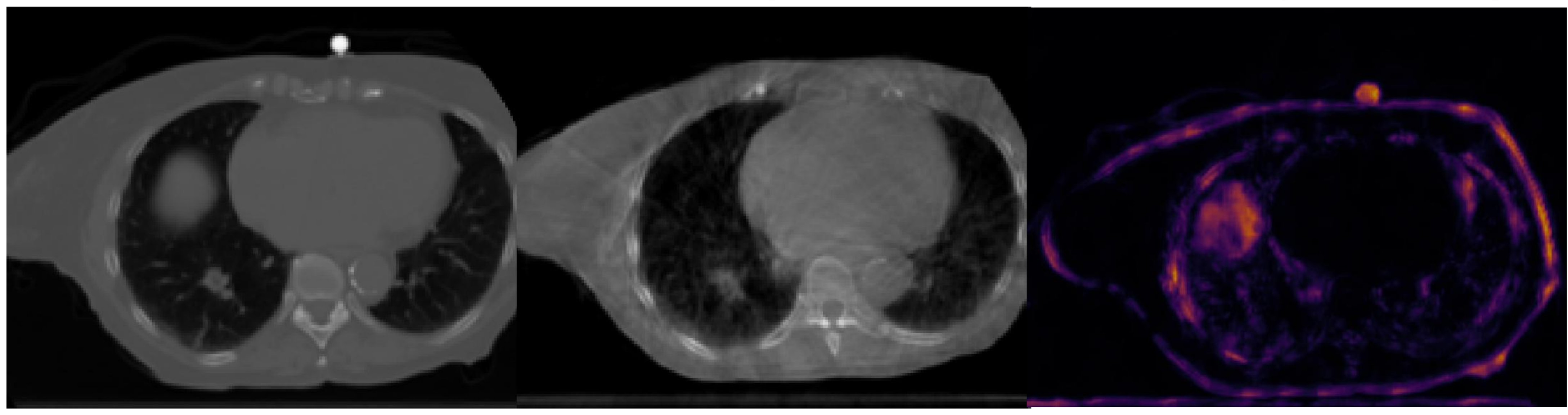
Best AUC Results: Model 2





Identified CT-CBCT Anomalous Volume

Simulation CT **Setup CBCT** **Anomaly Heatmap**



Discussion

- We developed self-supervised deep-learning models to detect a wide range of anomalies between the simCT and the daily CBCT
- The high ROC-AUC values between the two models detail the robustness of this approach across different treatment areas
- Future work includes the development of a model ensemble between Model 1 and Model 2 to combine the strengths of both approaches, and a retrospective study on previous treatment data to review for anomalies

Acknowledgements
This research was fully supported by the Department of Radiation Oncology at the University of California, Los Angeles

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