Generate Antarctic sub-shelf melt using recurrent neural network-based Generative Adversarial Models on pixel clusters

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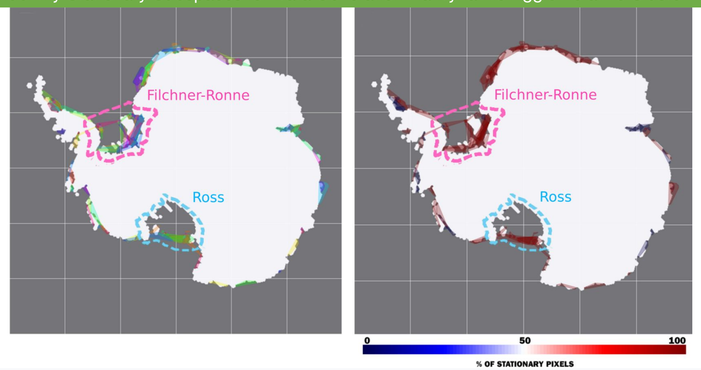
- Antarctic Ice Sheet ice loss accelerated by surrounding ocean's extreme warming over last 30 years The DOE E3SM v1.2 Cryosphere Configuration: Description and Simulated Antarctic Ice-Shelf Basal Melting→ dominant contributor to global sea level rise
- **Unknown**: How much ice loss due to anthropogenic changes and to **internal variability** [1]?
- **Goal:** develop/apply machine learning (ML) method(s) for data generation using limited model output (single realization) from *expensive* state-of-the-art Earth System model (E3SM) [2]
- **Previous work:** identified stationary subspaces (via customized hierarchical agglomerative clustering) of the input data that are both realistic (physically consistent) and representative of its complex spatiotemporal dynamics [3]
- **Current work:** results show TimeGAN can generate additional realizations of variable Antarctic sub-ice shelf melt that preserves the **temporal dynamics** and **stationarity** → **three metrics** (PCA [5], t-SNE [6], KPSS [7]) employed for evaluation of original model data and synthetic generated data

Approach: Identify Stationary Subspaces for Data Generation via Dynamic Agglomerative Clustering [3]



Prerequisites prior to data generation: identify individual subspaces in data that are:

1. *representative* of its spatiotemporal dynamics,
2. *realistic* in terms of consistency with physically observed dynamics, and
3. *stationary* over the entire time-series, regardless of the behavior of the data within each subspace relative to any other's (may vary independently over arbitrary time-scales)

Idea: construct dynamic hierarchical clustering pipeline to adaptively learn stationary subspaces, the number of which can grow or shrink in a data-driven fashion according to the data dynamics while simultaneously incorporating relevant prior domain knowledge (e.g. physical observations, problem setting).

Notation: Let $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ be 2 pixel locations given by their 2D coordinates on the Antarctic Ice Sheet. Note that each pixel spans *10* km. Ice melt flux time-series at these locations: $F_1 = (f_1^1, \ldots, f_1^M)$ and $F_2 = (f_2^1, \ldots, f_2^M)$, where *M* denotes the number of time-steps in the simulation, which for this data is a monthly resolution over *150* years, for *M = 1800* time-steps. Normalized versions denoted: $\widehat{F_k} = \frac{F_k}{max\, F_k}$ for $k \in \{1,2\}$, and the spatial-distance threshold denoted: d_{thr}^s.

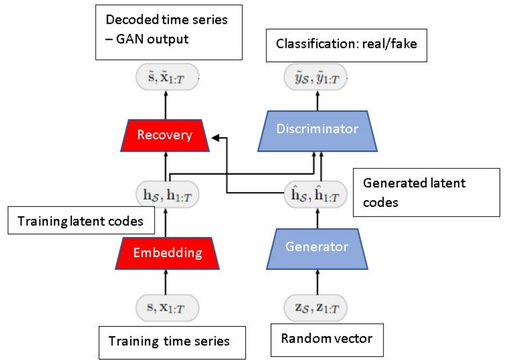
Aggregate Spatiotemporal Distance Criterion

$$d_{s,t}(p_1, p_2) = \begin{cases} \sum_{k=1}^{M} |\hat{F}_1(k) - \hat{F}_2(k)| & \text{if} \quad ||p_1 - p_2|| \le d_{thr}^s \\ +\infty & \text{else} \end{cases}$$

Stationarity: Evaluate the *stationarity of each identified cluster* using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) hypothesis test with the null hypothesis that the time-series is stationary around the mean. A cluster is considered to be stationary if the majority of its pixels pass the KPSS test.

Method: Time-series Generative Adversarial Network (TimeGAN) [4]

TimeGan Network Architecture

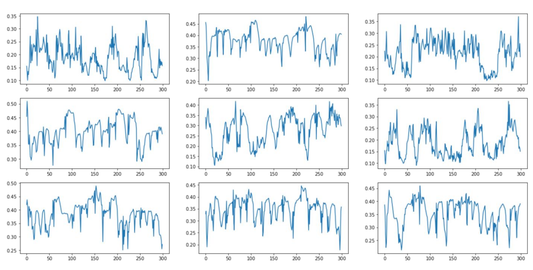


- **TimeGAN learns**: good generative model for time-series data that preserves temporal dynamics → new sequences respect original relationships between variables across time [4]
- Consists of four unique Recurrent Convolutional Neural Networks (RCNNs; e.g. LSTM, GRU): *embedder, generator, discriminator* and *recovery* RCNNs

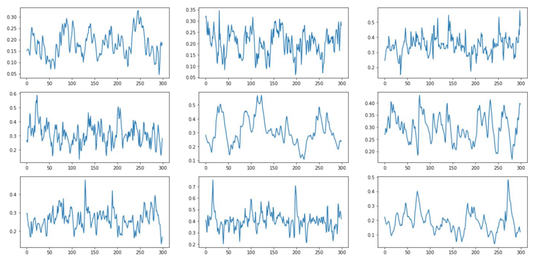
Data Generation: Examples of Original E3SM and TimeGAN Generated Data

Cluster 1 – gen seq. length 300 time-steps:

Generated data examples



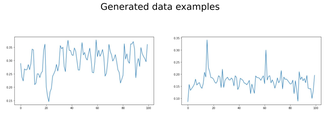
Original data examples



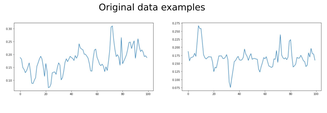
- **Generate data** from identified stationary clusters → train TimeGAN on individual cluster's respective time-series/pixels
- **Each cluster** ⇒ treated as its own independent data distribution for GAN to form generative model of

Cluster 2 – gen. seq. length 100:

Generated data examples



Original data examples

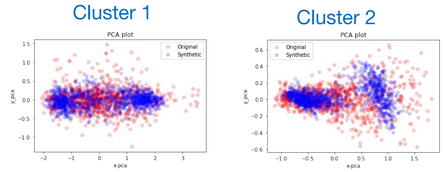


Evaluation: Qualitative and Quantitative Metrics of TimeGAN Generated Data

Assess consistency/similarity of the distributions of **generated data** vs. **input data**:

1. Principal Components Analysis (PCA) [5]

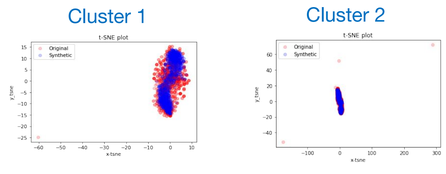
Cluster 1 Cluster 2



→ Flatten temporal dimension s.t. we can visualize data in 2D space: project all data onto the first 2 PCs of original data
→ **Shows**: significant overlap of and spread of input/generated data pts of both clusters 1 and 2

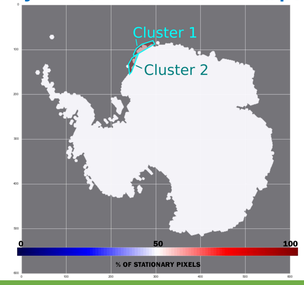
2. t-Dstributed Stochastic Neighbor Embedding (t-SNE) [6]

Cluster 1 Cluster 2



→ Method to quantify/visualize similarity of data – capable of retaining local structure of (high dimensional) data and revealing important global structure
→ **Shows**: significant overlap of clusters

3. Stationarity: KPSS Kwiatkowski–Phillips–Schmidt–Shin (KPSS) hypothesis test [7]



→ **Shows:** Cluster 1 and 2 both stationary according to KPSS with the null hypothesis that the data is stationary around the mean

Conclusions, Impact, and Outlook

- **Preliminary results** show TimeGAN can generate additional realizations of variable Antarctic sub-ice shelf melt that preserves the **temporal dynamics** and **stationarity**
- **Evaluation summary:** all 3 metrics show promise that the TimeGAN can produce data similar to the input data, both in terms of preserving temporal dynamics and stationarity → **PCA** and **t-SNE** show the input/generated data have similar temporal dynamics in a lower dimensional space, **KPSS** shows that the generated data retains the input data's stationarity
- This work addresses the general/pervasive problem of **data scarcity** in the climate sciences → far more computationally affordable than running climate model
- **Current ongoing work** investigating other time-series GANs [e.g. 8] and advanced discriminator functions for built-in non-parametric high-dimensional distribution comparisons [e.g. 9]

References
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