Deep Generative Modeling of Periodic Variable Stars Using Physical Parameters

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Main Goal

• Build a Generative Model that is able to create realistic observations of different types of variable stars.

• The model should consider stellar parameters and the variability class as inputs to generates a time series.

• Useful to:
  • Build training sets for supervised classification.
  • Explore how observing cadences impact variability studies at large scale including a wide variety of variability types.
What is a Deep Generative Model?

• A generative model describes how a dataset is generated, in terms of a probabilistic model. By sampling from this model, we are able to generate new data.

• A Deep Generative model (DGM) uses deep neural networks as functions.

• Examples of DGM are:
  • Generative Adversarial Networks (GAN)
  • Variational Autoencoders (VAE)
  • Normalizing Flows
AutoEncoder

Useful for:

- Data compression
- Feature extraction (Naul et al. 2018, Jamal & Bloom 2020)
- Dimensionality reduction

Figures by lilianweng.github.io/lil-log
Variational AutoEncoder

Generative Process

We want to know

But computing $p(x)$ is intractable, then using Variational inference we can approximate

And minimize the KL Divergence between them

Which leads us to the known expression for the VAE’s loss
Variational AutoEncoder

$z = \mu + \sigma \odot \epsilon$

$\epsilon \sim \mathcal{N}(0, I)$

An compressed low dimensional representation of the input.
Temporal Convolutional Networks (TCN)

- Causal convolutions (a)
- Dilated convolutions (a) -> improve receptive field
- Residual connections (b,c) -> improve convergence and stability of deeper models
VAE
Objective function

\[ L = \mathbb{E}_{q(z|x)}[\log p(x|z)] - \beta D_{KL}(q(z|x) \mid \mid p(z)) + D_{KL}(\hat{\sigma}_{mag} \mid \mid \sigma_{mag}) \]

Reconstruction Likelihood

KL-Divergence between encoder’s distribution and prior latent distribution

\[ p(z) \sim N(0,1) \]

KL-Divergence between reconstructed and real errors distributions

\( \beta \): tunes the importance of an orthogonal/disentangled latent space
65k Light curves
8 Variability classes (periodic only)
70% with Temp
5 % with stellar radius, luminosity and metallicity
-> we only used Teff, Mg, and Period.
Training and LC reconstruction

TCN layers:

• converge marginally faster

• Reached a smaller loss values w/r to GRU

Martinez-Palomera et al. 2020
Generating new light curves

Martinez-Palomera et al. 2020

Table 3. Latent-Physical space regression

<table>
<thead>
<tr>
<th>Generative Model</th>
<th>cVAE</th>
<th>cVAE-P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>0.863</td>
<td>0.794</td>
</tr>
<tr>
<td>Random Forest</td>
<td><strong>0.299</strong></td>
<td><strong>0.289</strong></td>
</tr>
<tr>
<td>Multi-Layer Perceptron</td>
<td>0.863</td>
<td>0.798</td>
</tr>
</tbody>
</table>

NOTE—Values correspond to the root-mean-square error for a validation set. Values in

![Image of graphs showing light curves and regression models]
Summary

• We successfully trained a VAE able to reproduce periodic time series

• Embedded physical parameters into the latent space

• Mapping (regression) between the Latent and Physical space enables to generate new light curves for a given set of stellar parameters.

• Generated light curves are conditioned to the variability class

• Generated light curves are “tagged” with the observing time, allowing to mimic different survey observing cadences

• Unfortunately, the training set did not allow for exploration of more stellar parameters.
Advertising

We are applying a similar approach of generative modeling with physical parameters to images of edge-on protoplanetary disks.

To hear more about it, tomorrow (Thu 18th), Zoie Telkamp (UCB grad) will present about this work during the lunch talks at the Astro Department (3:30 pm).

“Developing a physics-aware neural network to generate edge-on protoplanetary disk images”
Thanks