# Lab11

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## 1 Part 1: Summary & Comments

In this paper, Physics-informed machine learning, the authors summarized pathways to embed physics information into machine learning and deep learning approaches, demonstrated the advantages of physics-informed learning, listed the available software and feasible applications, investigated current limitations, and finally provided future directions in the field.

First, three different pathways to embed physics were provided, including observation bias, inductive bias, and learning bias. Observation bias is probably the main reason for the success of current machine learning models, which are based on a large amount of observation data to cover the input domain and to reflect the underlying physical principles. The observation data may be collected from experiments or simulated by computational models, which may be expensive and time-consuming. With inductive bias, specific architectures or kernels are designed to form constraints with physics information. The specific design is limited to tasks, and still faces challenges in complex tasks, though robust in simple and well-defined physics. The use of learning bias is to develop loss functions based on physics, which could be considered a special use case of multi-task learning. This approach ensures flexibility when incorporating more general domain-specific knowledge. Then several examples of hybrid approaches were provided with their unique advantages on certain types of tasks. The connections between NNs to kernel methods and classical numerical methods were also discussed. According to the authors, NNs can be rigorously interpreted as kernel methods, and the use of a kernel-based lens could benefit the analysis of NNs methods. DNNs are also analogous to classical numerical methods, which provides insights into the meta-learning approach.

The authors then provided the merits of physics-informed learning, which are the capabilities of dealing with imperfect physics, data, and even problems, the strong generalization in the small data regions, the help of understanding and interpreting deep learning, the capability of modeling high-dimensional distributed data, and the qualifications of uncertainties due to the physics, the data, and the learning model. Then, after listing several applications in different scientific domains and available software, the authors discussed the way to decide model, framework, and algorithm to use. They claimed that currently, no solid answer exists, and they may be decided by previous experiences, but meta-learning techniques could automate the process in the future.

The authors then investigated potential limitations. They first discussed the struggle to use physics-informed learning in multiscale and Multiphysics problems. The problem may be addressed by developing new techniques but may also increase time consumption. Another limitation is the lack of scalable and parallel training algorithms to speed up the learning, as well as efficient operators to compute high-order derivatives. The difficulty in collecting full-filed data and designing benchmark datasets also causes limitations in evaluating physics-informed learning. The last limitation promoted by the authors is the lack of theoretical understanding of NNs under constraints. Three types of errors, which are approximation error, optimization error, and generalization error, should be mathematically quantified, but are still in investigation.

Finally, the authors provided several future directions, including the application to digital twins, the transformation, fusion and interpretability of data and models, and the development of useful representations.

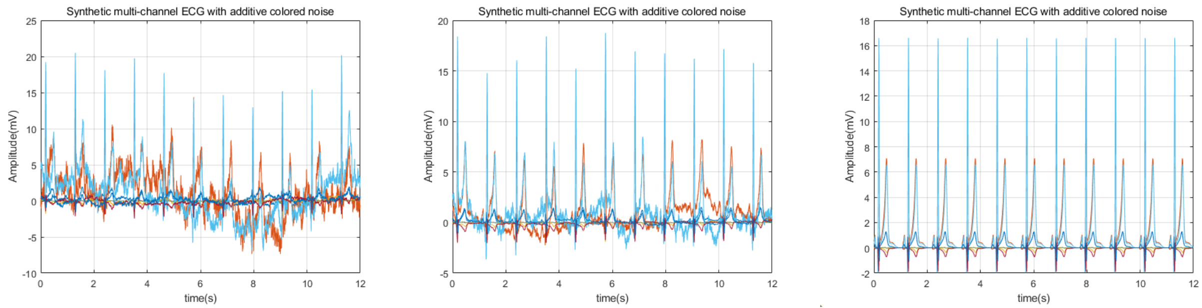
The entire paper is well-structured and informative which is elucidated from the reason to embed physics, to the methods of embedding physics into models, then to practical implementation, applications, and limitations of physics-informed learning, and finally to the insights of future research. The claims made by the authors were provided with sufficient references and were convincing. Due to the outstanding performance of physic-informed learning in each domain presented in the paper, I would consider to utilize it in my future research.

## 2 Part 2: Simulate Pandemic

Link to GitHub Repo: https://github.com/RuochenKong/BMI500_Lab11
The source codes and test cases are in simulate_pandemic.ipynb

## 3 Part 3: Simulate ECG

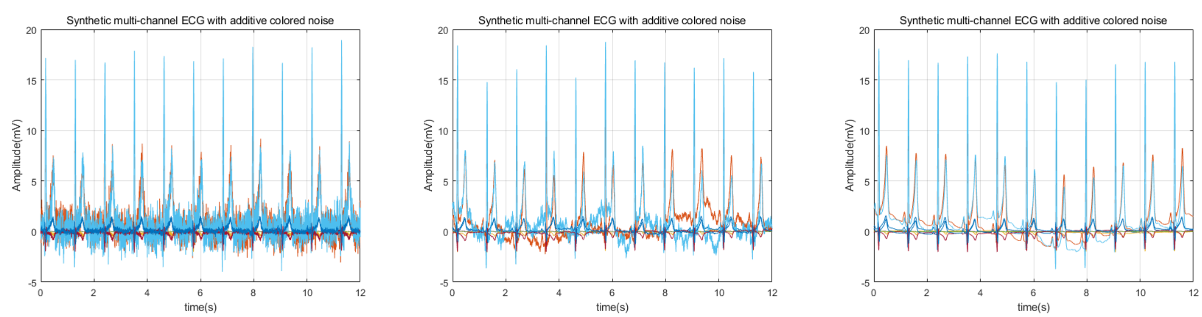
The simulation is based on the dipole generator and colored noise as in file **testECGGenerator1.m**. Several parameters used in the model could change the output of the simulated signals. **N** and **fs** are the numbers of generated signals and sample rates, which could be changed based on personal choices. The locations of the heart, the positive electrodes, and the negative electrodes should be specified in **heartlocation**, **ElecPos**, and **ElecNeg**, before the simulation. The **snr** is the ratio between signal to noise. As shown in the Figure 1, the larger the **snr**, the lower the degree




(a) snr=1 (b) snr=10 (c) snr=100

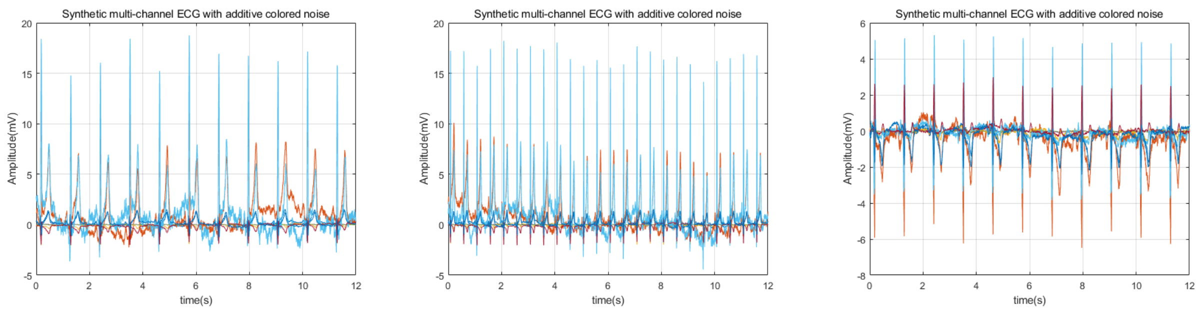
Figure 1: The effect of using different value of snr

of noise and the smaller fluctuations of the P, Q, R, S, and T points. The **beta** parameter controls the level of colored noise, which has a power spectral density per unit of bandwidth proportional to $\frac{1}{f^{\beta}}$. Thus, as shown in Figure 2, the larger the **beta**, the smaller the noise. The difference between the **snr** is that it is unable to change the 5 peak or trough points. The heart rate is determined by **F**, which represents the number of beats in each second. **R0** represents the rotation of the heart, which is more useful in generating fetal ECGs and typically remains zero for the normal condition. Figure 3 shows the effect of changing **F** or **R0**. Then, the Figure 4 shows that theta0 decides where the signal starts. Finally, 3 sets of parameters, which are $\theta_i^{\{x,y,z\}}$, $\alpha_i^{\{x,y,z\}}$, and $\beta_i^{\{x,y,z\}}$, contribute most of the simulating model. The simulation is based on a dipole vector which is a summation of Gaussian functions with different rotational angles $\theta_i$, amplitudes $\alpha_i$, and widths $\beta_i$ in each direction. Deciding on these parameters requires domain knowledge, so they should be changed by analyzing real-world signals or by references. By changing these parameters, artificial ECGs could be generated which could be hardly distinguished from real-world records.



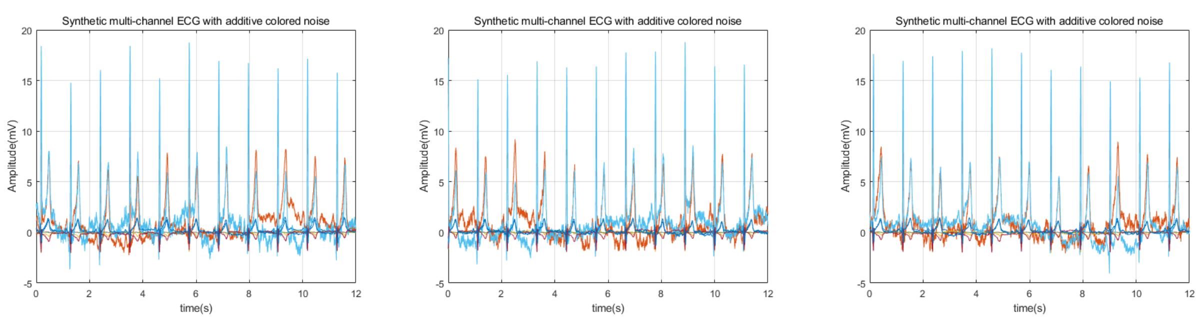

(a) snr=1 (b) snr=10 (c) snr=100

Figure 2: The effect of using different value of beta




(a) F=0.9, R0 = (0,0,0) (b) F=2, R0 = (0,0,0) (c) F=0.9, R0 = (-3*$\pi$/4,0,-$\pi$/2)

Figure 3: The effect of using different value of beta




(a) theta0 = -$\pi$/3 (b) theta0 = -2$\pi$ (c) theta0 = -$\pi$/4

Figure 4: The effect of using different value of beta