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## Potential Quotes for Final Report

*"When an electromagnetic wave encounters an object it scatters, with some energy being transmitted into the object and the rest propagating in a variety of directions depending on the material composition and local geometry. A precise knowledge of the scattering phenomenon is desirable for a variety of applications, such as medical imaging, radar and wireless communications. Numerical techniques such as the method of moments give highly accurate results, but are computationally expensive. An emerging alternative is the use of machine learning tools that can be trained using a training set of data covering a sufficiently wide feature set (i.e. problem geometry, material, frequency etc). This project will use an in-house, Matlab-based, implementation of the method of moments to train an artificial neural network to solve the problem of EM scattering from convex dielectric bodies." Conor Brennan, Project Description*

*"Fredholm equations arise in many areas of science and engineering. Consequently, they occupy a central topic in applied mathematics. Traditional numerical methods developed during the period prior to the mid-1980s include mainly quadrature, collocation and Galerkin methods. Unfortunately, all of these approaches suffer from the fact that the resulting discretization matrices are dense. That is, they have a large number of nonzero entries. This bottleneck leads to significant computational costs for the solution of the corresponding integral equations" [1].*

*"We have forgotten to observe. Instead of observing, we do things according to patterns." - Andrej Tarkovsky*

## New References

The references are not found in the literature review but may prove useful in completing the project.

### Sources for ML for General Forward Problems

[2] – Brunton is a lead in the area so this is a key text.

[3] – Although mentioned in the literature review, the examples of the possible uses for ML in the forward problem remains better than most texts, until [4] was found: in general science applications, Data Analysis to derive physical models from experimental data by learning distributions from data [ref Meh+19]; Combined Methods to improve

conventional computational methods [ref FDC20]; surrogate models to completely replace conventional computational methods in specific situations [ref FDC 20]; Model Order Reduction in fluid mechanics [ref BNK20].

### New sources for ML with EM Scattering

[4] – Logged

[5] – Not read yet.

### State-of-the-Art for Conventional Numerical Methods

[6] – Circulant matrices and pre-conditioners are a key aspect to accelerating the conventional problem.

[7] – Preconditioners

[8] - Chapter 4, 8, 13, 14. THIS IS CUTTING EDGE VEFIE

### Monte Carlo References

[9] – Not going to have time to investigate but Section 2.3 covers Neumann Series expansion.

### Numerical Approaches & Infusion

[10] – Started reading, the student believes that there is opportunity for deep learning infusion here.

[11] – Not read yet.

[12] – Not read yet.

### Thesis & Code Management

[13] – To implement

### ML Experimental Design

[14] – To be read

[15] – To be read

### To Be Published

Soon

<https://www.nature.com/collections/hdjhcifhad/how-to-submit>

2023 August

[16]

June 2024

<https://www.asme.org/publications-submissions/journals/administration/call-for-papers/special-issue-on-physics-informed-machine-learning-for-advanced-manufacturing>

### Sources to iteratively check

- <http://m-dml.org/publications.html>
- <https://aces-society.org/emschool/>
- <https://gtr.ukri.org/projects?ref=EP%2FS003975%2F1>
- IEEE Press Series on Electromagnetic Wave Theory
- <https://www.springer.com/series/13885>
- <https://www.eigensteve.com/publications>
- <https://www.eucap2023.org/>

- <http://aemjournal.org/index.php/AEM/index>
- <https://research.com/journals-rankings/computer-science/computer-vision>
- [https://scholar.google.it/citations?hl=it&user=CZKB5sEAAAAJ&view\\_op=list\\_works&sortby=pubdate](https://scholar.google.it/citations?hl=it&user=CZKB5sEAAAAJ&view_op=list_works&sortby=pubdate)
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