

Sources:

## Key References and Inspirations:

### 1. Research Paper: "Lagrangian Neural Networks" by Cranmer et al., 2020

- DOI: [10.48550/arXiv.2003.04630](https://doi.org/10.48550/arXiv.2003.04630)
- This foundational paper introduces the concept of LNNs, explaining how to structure a neural network to learn dynamics by leveraging the Lagrangian formulation.
- Key ideas include using the Euler-Lagrange equations to compute dynamics and enforcing physical consistency during training.

### 2. Lagrangian Mechanics Textbooks

- Standard physics resources such as:
  - *"Classical Mechanics"* by Herbert Goldstein
  - *"Classical Dynamics of Particles and Systems"* by Thornton and Marion
- These provide a detailed understanding of Lagrangian mechanics, including deriving equations of motion for simple systems like pendulums and sliding blocks.

### 3. PyTorch Documentation

- Official PyTorch documentation on:
  - Automatic Differentiation (autograd)
  - Neural Networks API
- PyTorch's autograd is central to computing derivatives needed for Lagrangian dynamics.

### 4. Machine Learning for Physics

- Tutorials and blog posts discussing physics-informed neural networks (PINNs) and their application to classical mechanics problems.
- Example: Blogs from DeepAI, Medium, or GitHub repositories focused on physics-informed ML.

### 5. GitHub Projects

- Open-source implementations of LNNs and Hamiltonian Neural Networks (HNNs), such as those found in repositories like:
  - [Cranmer's GitHub Repository for LNNs](#)