Future Prospects for Data-Driven Methods in Materials Science
Outline

I. OUTLINE

- Framing AM as a sub-field of materials science: other fields have tackled similar problems
  - High-throughput studies have long been used in materials science [1]
  - Multi-scale modeling has also been around in materials for a while [2]
  - Machine learning has been adopted in materials recently
  - **AM users do not need to reinvent the wheel (completely) when adopting data-driven methods for AM; they need to look to previous investigations in materials science**
- Data driven/machine learning has been picking up in materials
  - Promoted by materials genome initiative [3]
  - Examples:Photovoltaic materials [4]; Dialetric Materials [5]; Molecule Design [6]; [7]
  - Adoption of machine learning in AM should take into consideration how other fields are using it **so that standard applications of ML in materials science can be developed**
  - Review articles of ML for mat sci: [8–11]
  - **The AM field, along with other fields of mat sci, should evolve toward standard practices in the use of machine learning**
  - Maybe a good place to talk about standard data formats (e.g. the PIF)
  - The 'standard' adoption of ML (and what it would look like) is something that Branden, Brice, etc., may have insight on
- Moving AM toward a database-driven approach
  - Other fields are already adopting databases: Mat Proj [12], AFLOW [13]; OQMD
  - **Machine learning models can be improve with more data, therefore AM data should be widely & publicly accessible**
  - Discuss infrastructure necessary for use of AM databases

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