SPARK Program Student Research Project
Summer 2022

Optimizing Composite Materials in Additive Manufacturing for Fused Filament Fabrication with Deep Learning Techniques

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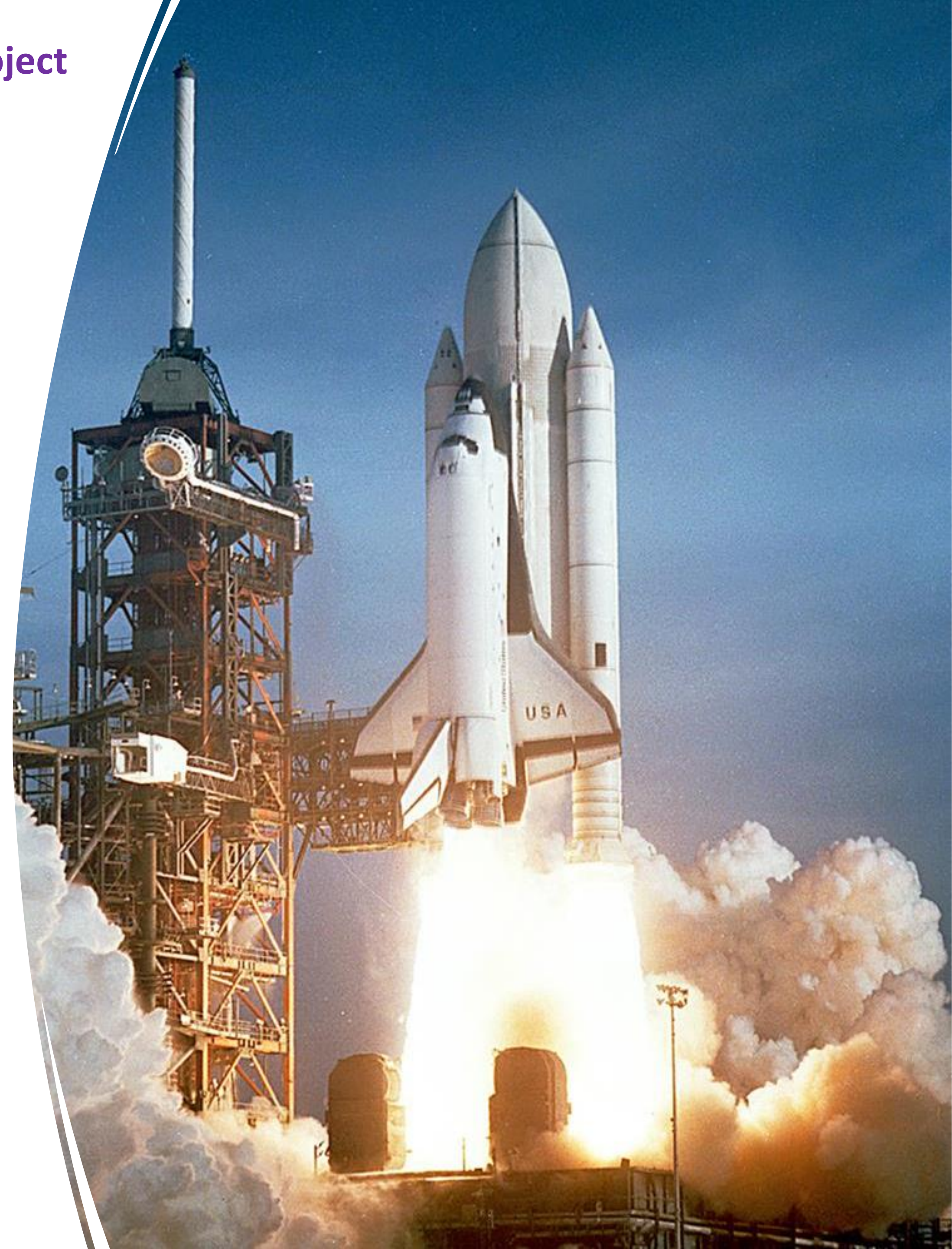

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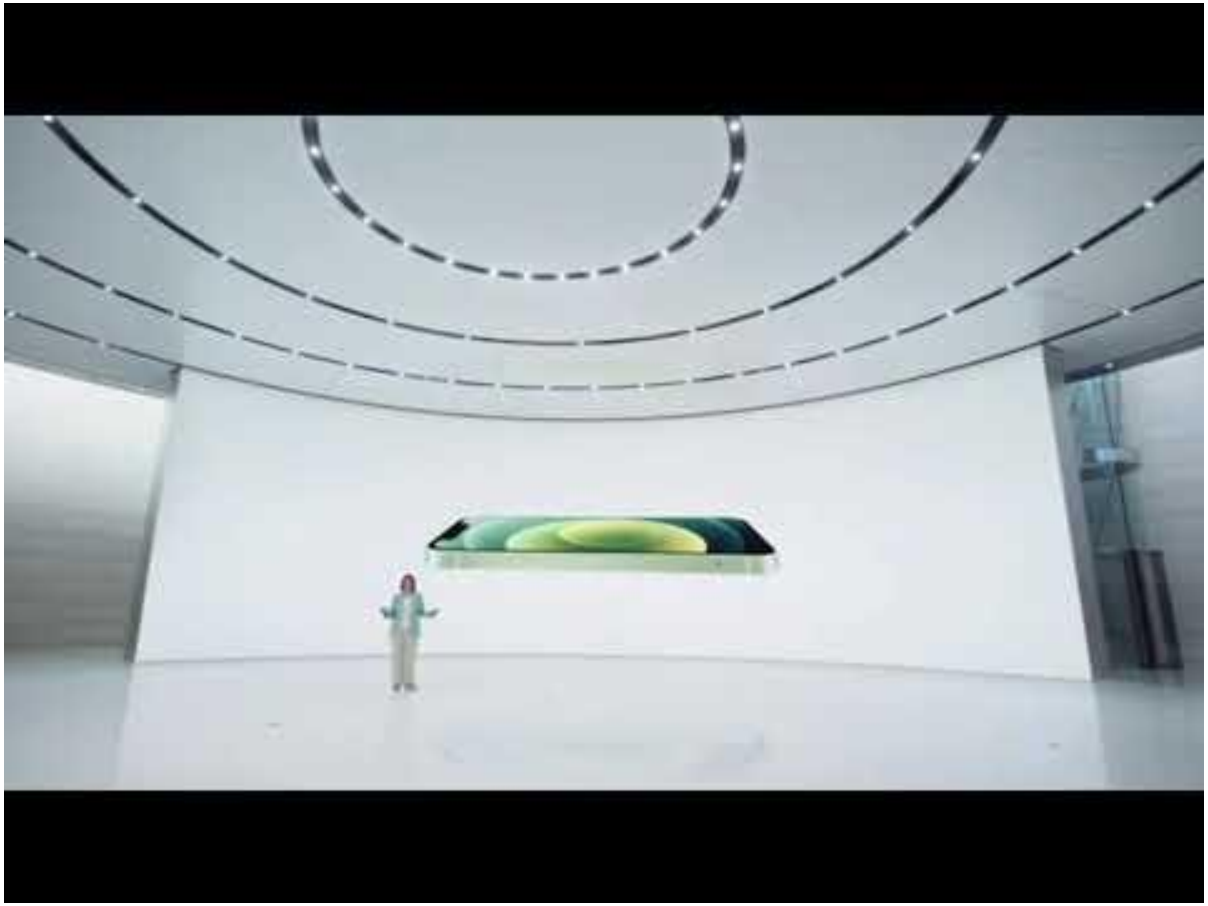
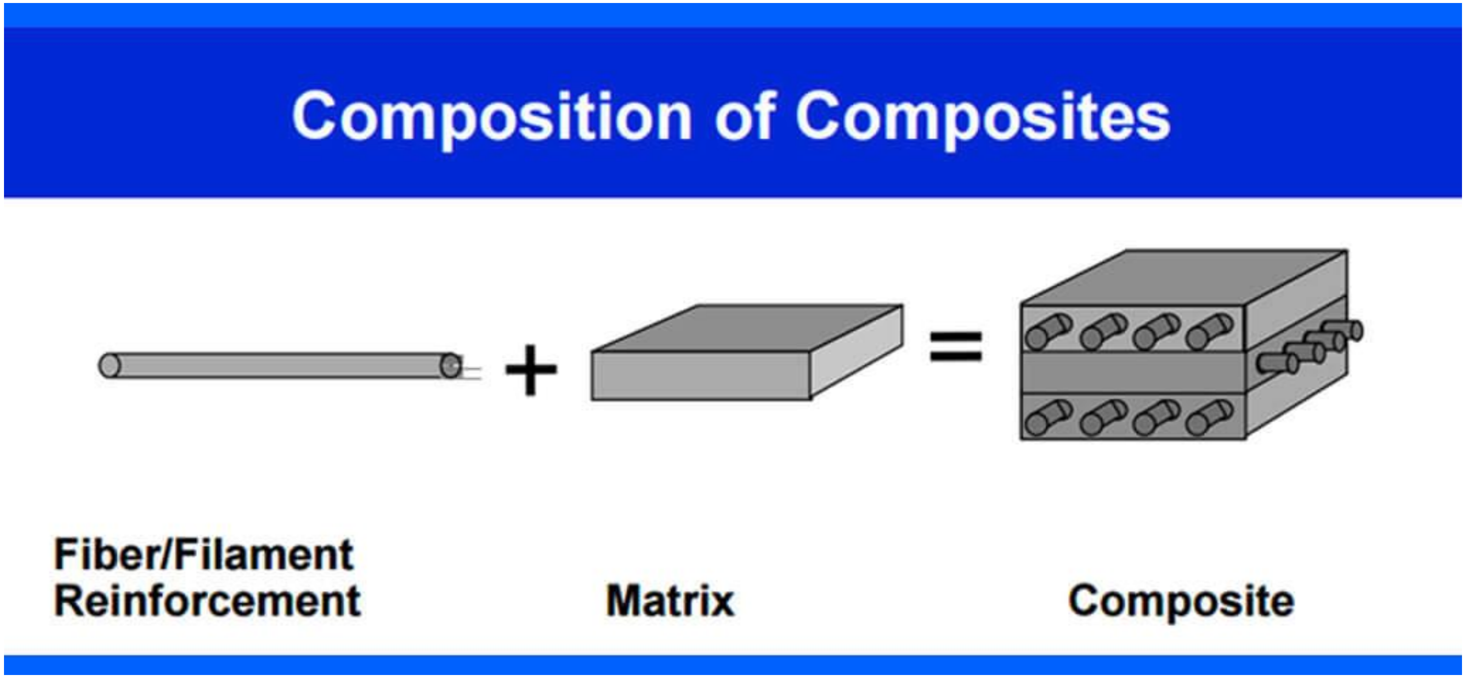
Current Applications - iPhone 12



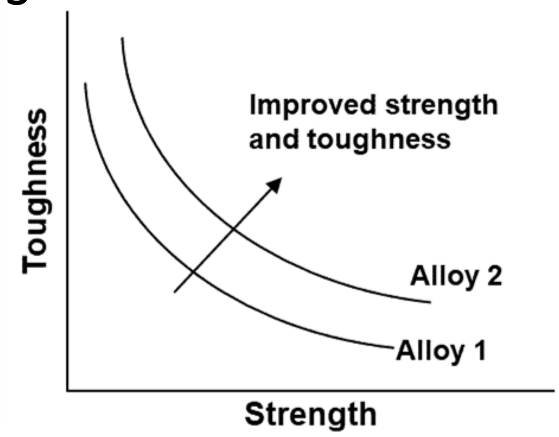
Composite Structure



- A composite is comprised of a Matrix Material and an Inclusion Material.
  - e.g. Carbon Fiber → Thin Carbon Reinforcements + Epoxy/Resin Base
- For this experiment
  - Matrix: PLA/ABS
  - Inclusion: Independent Variable

Why are Composites Important?

- Enhanced Properties over regular materials
  - **Fracture resistance → Ceramic Shield**
  - Toughness
  - Strength
  - Formability



- High Performance Applications
  - Helmets to prevent Concussion

- Waste Reduction
  - Recyclability
  - Greater strength = less material needed

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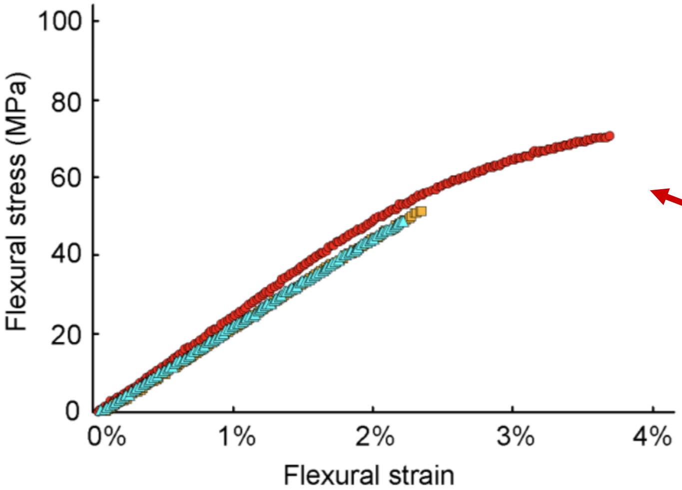
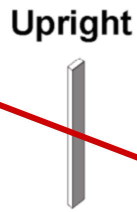
Enhanced Properties Figures

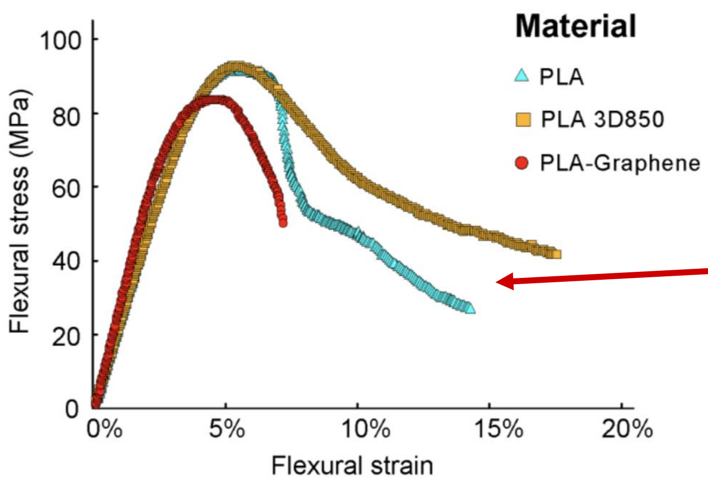
slope = Young's Modulus

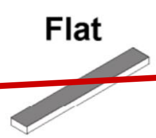
Area under the Curve = Toughness





Composite with Graphene can withstand more stress





Both PLA composites have greater toughness

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Feature Engineering

- Not only can we use collected data from our experiments/dataset, we can also use known Mechanical & Thermal properties of the materials we are using

Matrix Material (e.g. PLA)		Inclusion Material	
Thermal Conductivity	0.0439	Particle Shape	spherical, ellipsoid, etc.
Melting Temperature	152	Particle Size	relevant dimensions of particle
Glass Transition Temperature	60	Dispersion	# of materials contacting the surface
Melt Mass Flow Rate	6.09	Volume Fraction	Inclusion Volume/Total Volume

- Domain expertise tells us these are relevant to the final composite properties

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Original Dataset

Setting Parameters:

- Layer Height (mm)
- Wall Thickness (mm)
- Infill Density (%)
- Infill Pattern ()
- Nozzle Temperature (C°)
- Bed Temperature (C°)
- Print Speed (mm/s)
- Material ()
- Fan Speed (%)

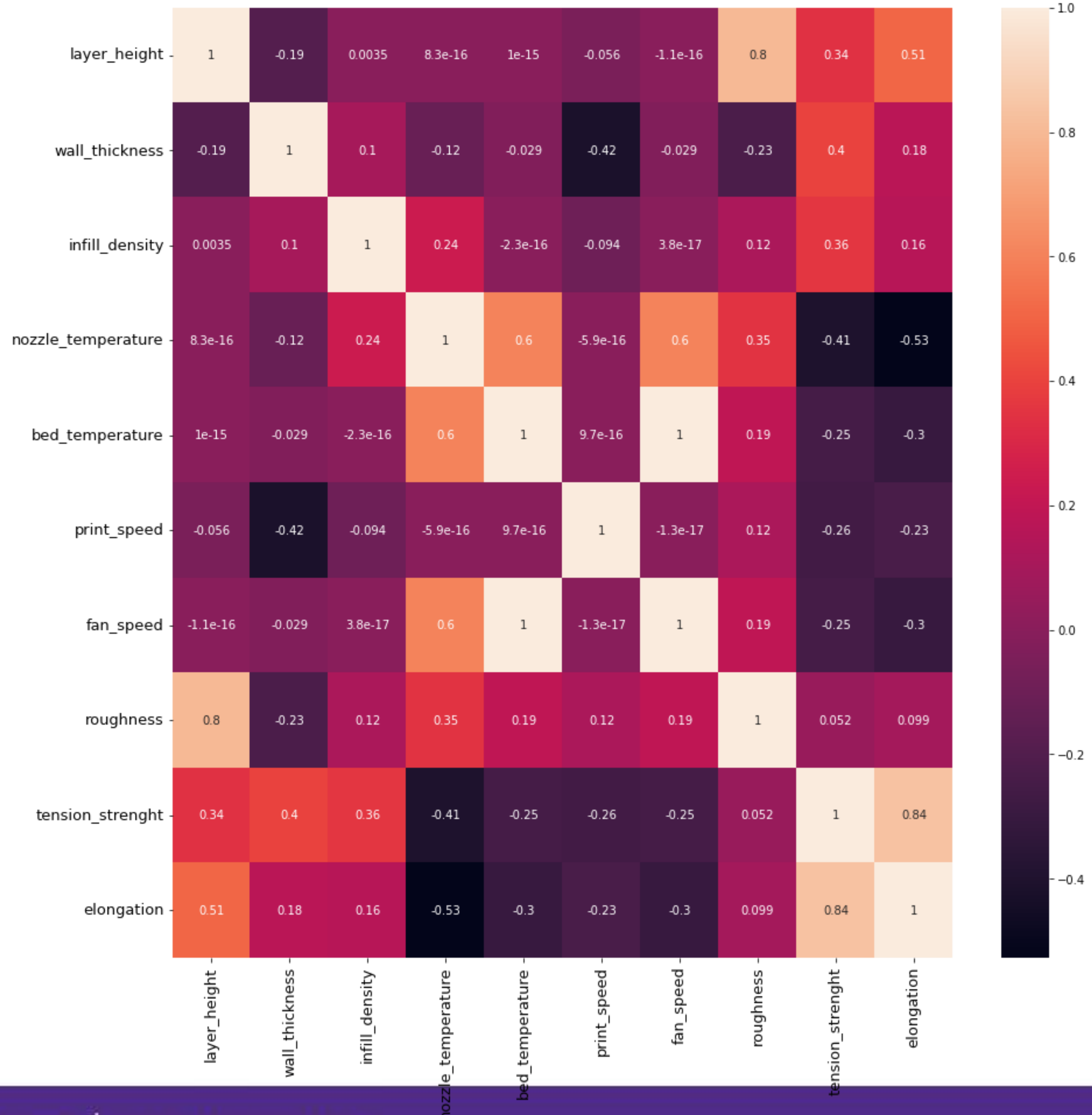
Output Parameters: (Measured)

- Roughness (µm)
- Tension (ultimate) Strenght (MPa)
- Elongation (%)

# layer_height	# wall_thickness	# infill_density	infill_pattern	# nozzle_temperatu...
0.02	8	90	grid	220
0.02	7	90	honeycomb	225
0.02	1	80	grid	230
0.02	4	70	honeycomb	240
0.02	6	90	grid	250
0.02	10	40	honeycomb	200
0.02	5	10	grid	205
0.02	10	10	honeycomb	210
0.02	9	70	grid	215
0.02	8	40	honeycomb	220
0.06	6	80	grid	220
0.06	2	20	honeycomb	225
0.06	10	50	grid	230

https://www.kaggle.com/datasets/afumetto/3dprinter

Correlation Matrix



Material Features + 3D Printer Data = Good Data?

Not Exactly…

Limitations

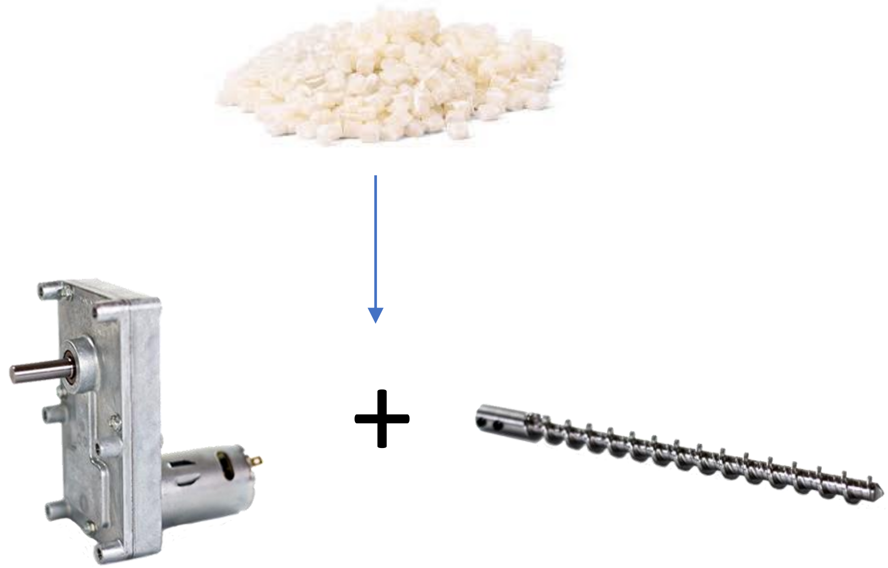
Data we found

- Homogeneous material
- 3D printing **not** Extruder data
- Steady state processing conditions
- **small data set ~50 Data Points**

Data we need → Filament Extruder

- Composite with inclusion material
- Potentially dynamic process (if 3D printing)

Hardware to Collect Data

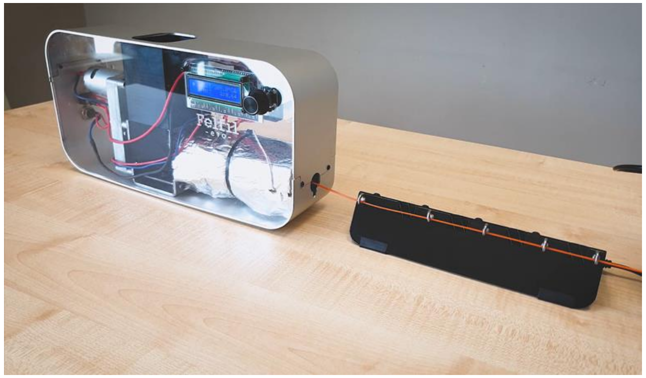


What is an Extruder?

- A machine that is able to create filament for a 3d printer using pellets of any material
- Motor + Extrusion Screw
- Outputs spools of Filament

Why use an Extruder?

- Reusability
- Cost
- **Customizability**



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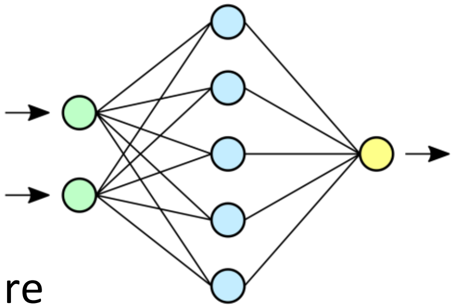
Feed-Forward Neural Network

- Input Parameters
  - Layer Height
  - Wall Thickness
  - Infill Density
  - Infill Pattern
  - Nozzle Temperature
  - Bed Temperature
  - Print Speed
  - Fan Speed
  - Features:
    - ~~Thermal Conductivity~~
    - Melting Temperature
    - ~~Glass Transition Temperature~~
    - ~~Melt Mass Flow Rate~~



- Output Parameters
  - Tensile Strength
  - Elongation

- Network Structure:
  - 9 Inputs, 2 Outputs
  - 3 Hidden Layers
  - 30 Hidden Neurons/Layer
  - Batch Size - 20
  - Adam Optimizer
  - MSE Loss Function
  - Min-Max Normalization

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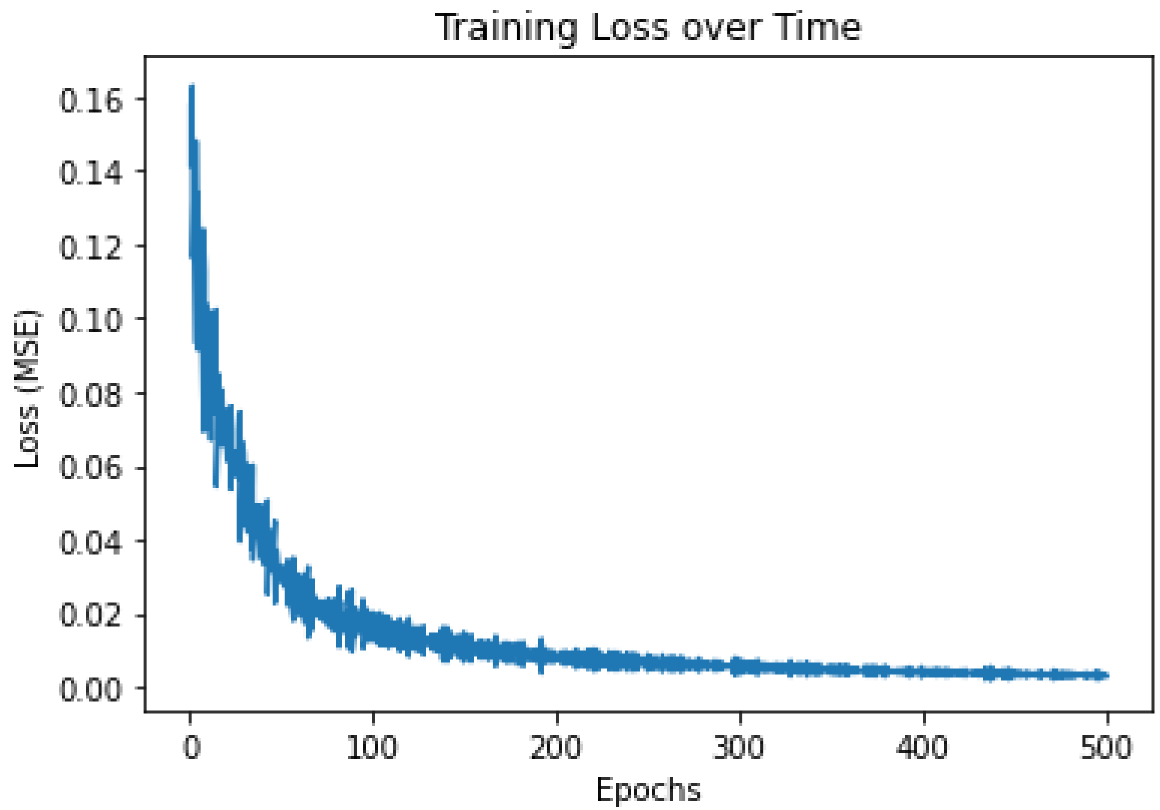
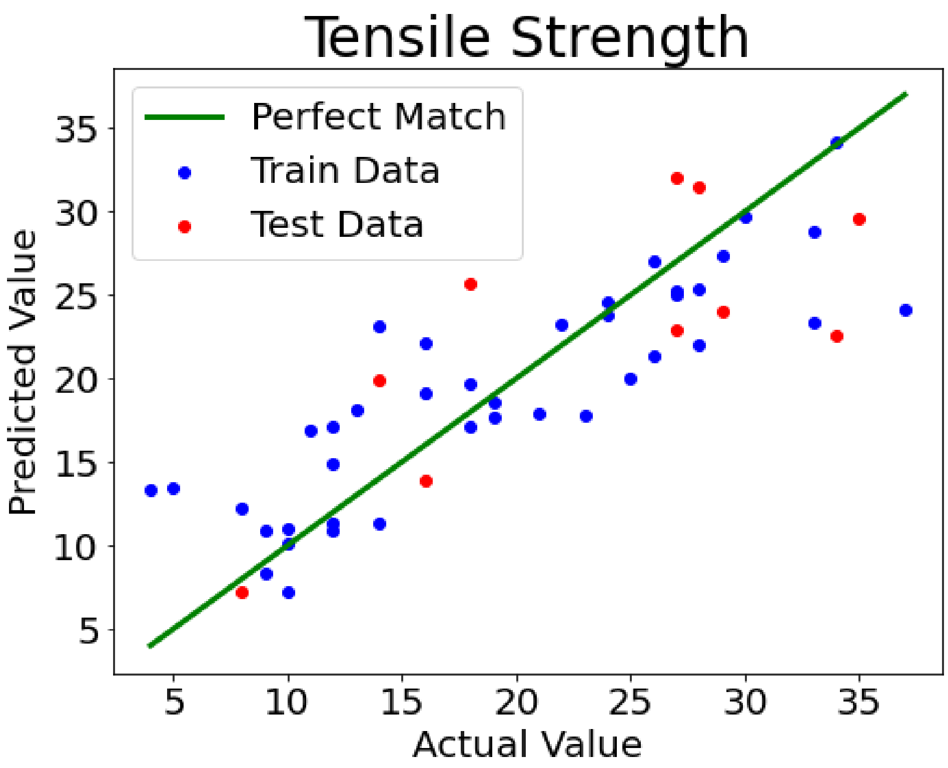
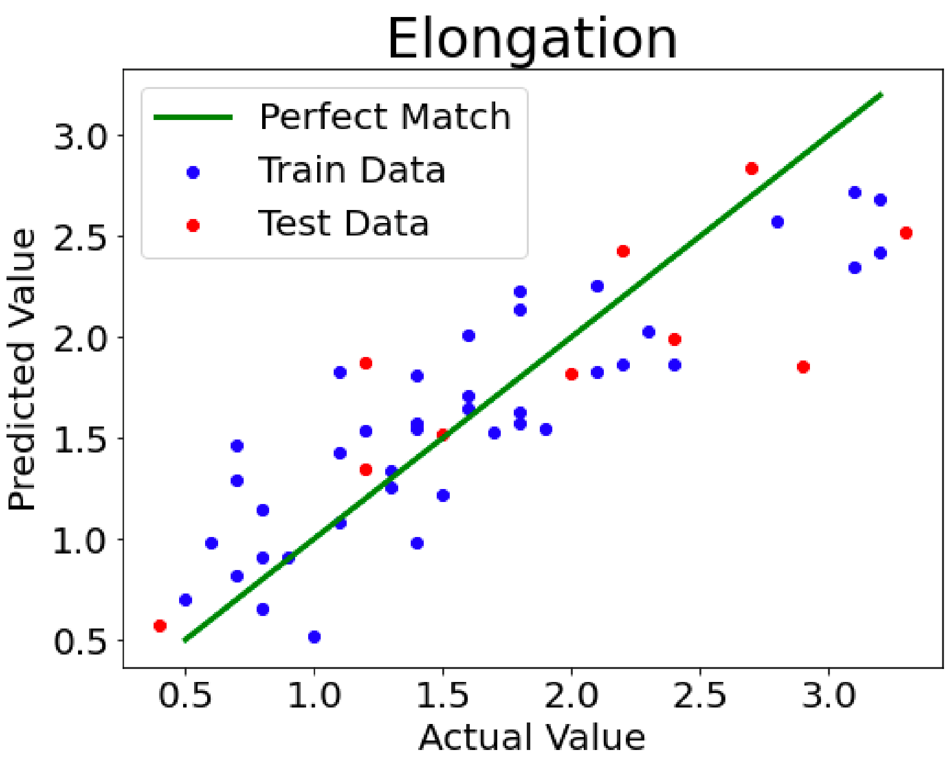
Results

Training Loss Function



Actual vs. Predicted





Overfitting Control

```
[4] # Split Train and Test Data
    test_count = 10

    import random
    idx_order = list(range(features.size(0)))
    random.shuffle(idx_order)
    idx_train = idx_order[:-test_count]
    idx_test = idx_order[-test_count:]

    train = torch.utils.data.TensorDataset(features_n[idx_train], targets_n[idx_train])
    test = torch.utils.data.TensorDataset(features_n[idx_test], targets_n[idx_test])
    train_loader = torch.utils.data.DataLoader(train, batch_size = batch_size, shuffle = True, num_workers=2)
    #test_loader = torch.utils.data.DataLoader(test, batch_size = batch_size, shuffle = False, num_workers=2)
```

- Random Test Split to Validate Data – Similar to k-fold cross validation
- Regularization:
    - Limiting the magnitude of the weights through weight decay

```
# loss and opimizer
criterion = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate, weight_decay = 0.01)
```

Progress + Timeline

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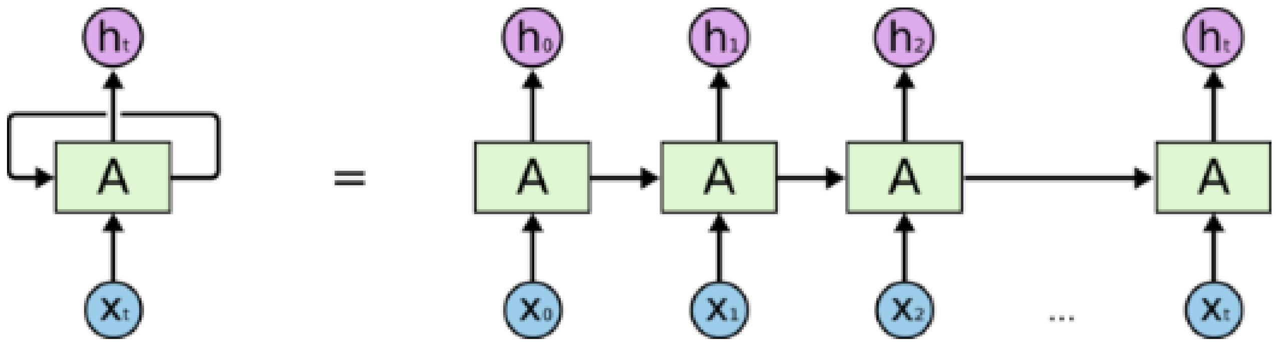
RNN



An unrolled recurrent neural network.

3D printing process

An RNN could map sequential and dynamic AM process parameters to resulting property

Potential to control constitutive properties (RPM, Temperature) throughout a part by manipulating the printing process during AM

Future Goals

- Finish the Extruder, and test with different Inclusion Materials
- Collect data to expand the current dataset and fit our parameters
- Create a Dataset that has more versatility
  - Predict tensile strength/elongation of unknown material

Thanks!

Questions?