Carbon Cut

Building Greener Futures

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The CarbonFighters

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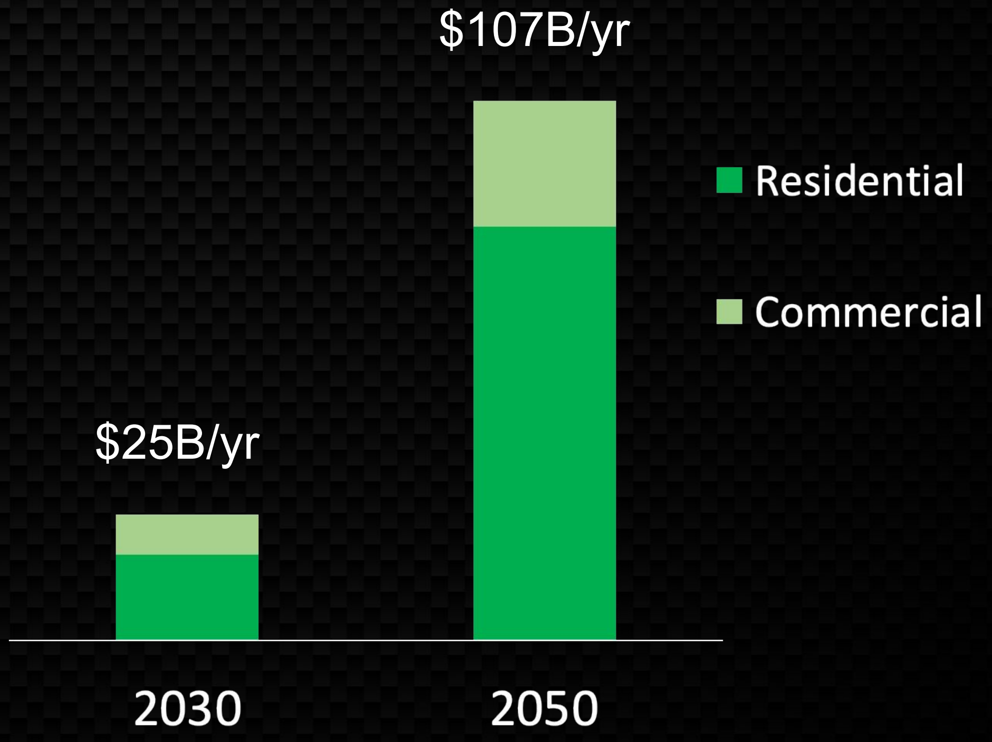
$107 Billion Per Year Savings in the Power Sectors



National Power System Cost Savings, Lawrence Berkeley Lab

CHALLENGE

Decarbonizing buildings is critical, but current approaches are inefficient and lack direction.

U.S. CO_2 Emissions: **4.7** Gt/y

↓

40% Attributable to buildings

Decarbonizing the building sector requires significant planning and prioritization.

Large amounts of building data are required to accomplish this efficiently.

Navigating complex decarbonization planning

Buildings

105,000,000

2,000,000

Types

Single Family

Small Multifamily

Large Multifamily
20+ Wood

Large Multifamily
5-19

Large Multifamily
20+ Steel

Strategies

Electrification
-Heat pumps
-Variable refrigeration

Energy efficiency
-Insulation
-high-performance windows
-air sealing/ weatherization

Source: Mass.gov, ConstructionPhysics.com

Limited availability of building metadata hinders precise targeting of decarbonization projects.

Insulation
Windows
Heating
Cooling
EV / PV
+ More

Introducing…

Carbon Cut

Using very limited data we help planners and decisions makers prioritize building decarbonization projects.

Predict CO2 emission reductions of 10 different building upgrades

Estimating building configuration (size, type, heating, cooling, etc)

Open source

Scalable: Phase I: Residential, Phase II: Commercial

Applicable for both Nonprofit and For Profit organizations

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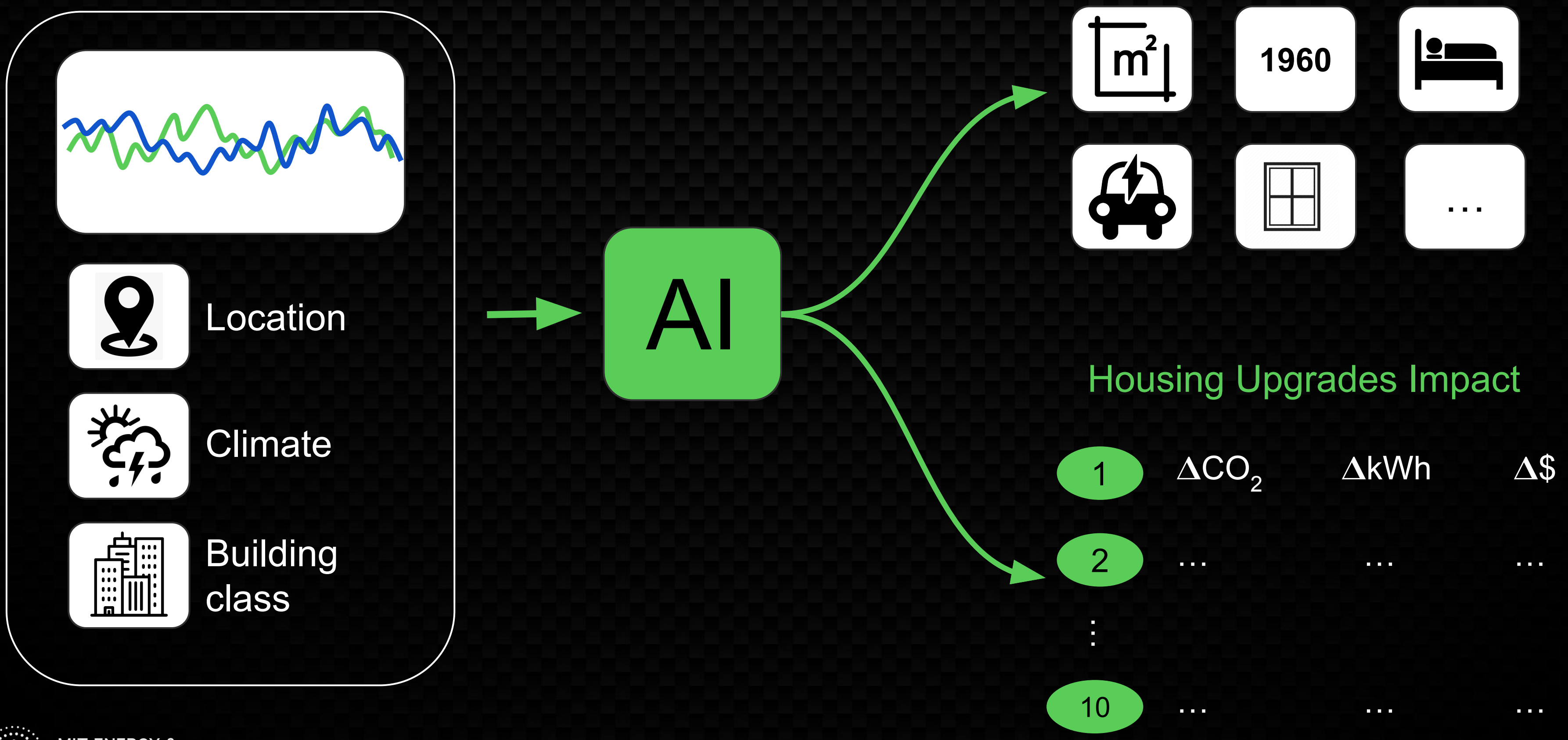
How do we do it?

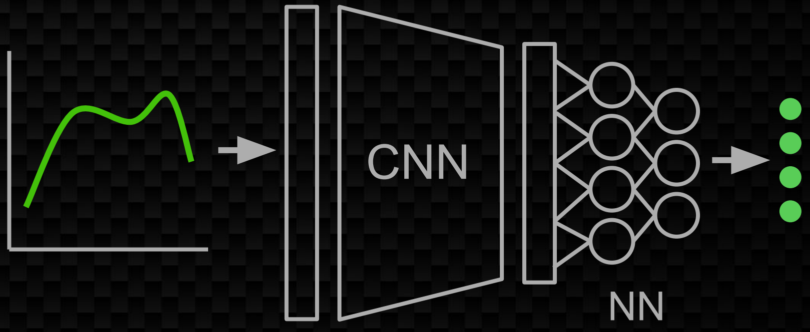


Technical Overview

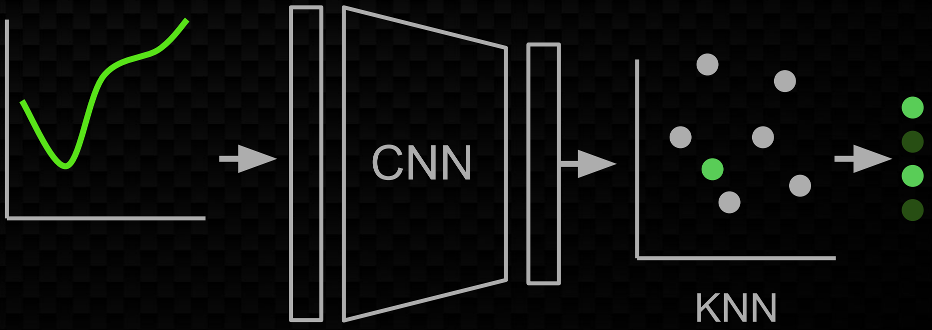
Res
Stock
2022

Within 10%!

Prediction Model

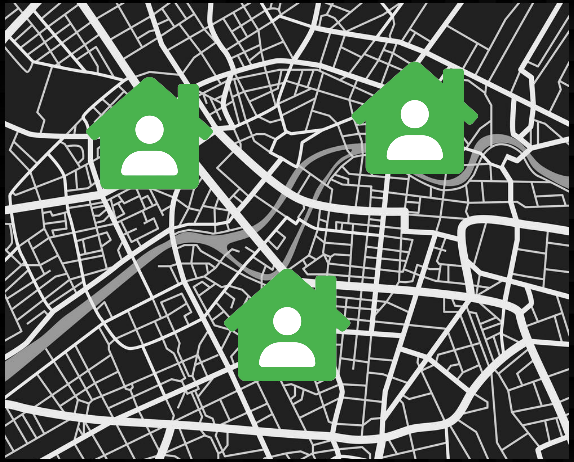


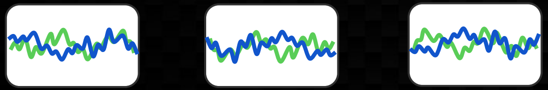
Estimation Model



Case study

Building Owner





Objectives

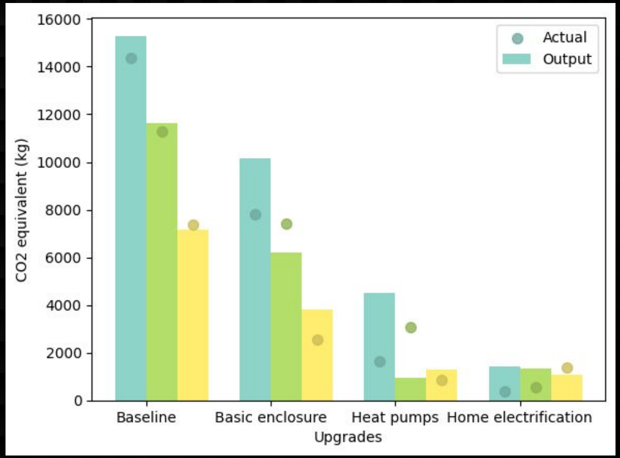
Decarbonization incentives

Energy Savings

Net zero

Results

Impact of Upgrades on Emissions



(Actual model output!)

Technical Report

CarbonFighters - Carbon Cut Technical Writeup

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Keywords:
Artificial Intelligence
Climate Change
Decarbonization
Prediction

Abstract **Technical Mission**: To make an open-source resource for making high-quality building decarbonization characteristic predictions from simple and common data points.

 Submitted: 12 November 2023

1. Approach

Train a machine learning architecture on the Department of Energys ResStock dataset to learn:
- Given a load shape, what are the predicted carbon reductions for ten different prespecified decarbonization schemes?
- Given a load shape, predict key characteristics about the house that are useful in the energy transition (square footage, EV usage, window type, etc.)

2. Data

We are using two parts of the ResStock dataset. We restricted ourselves to half the Massachusetts dataset to have reasonable data processing time, as the full US dataset weighs several terabytes.

On one side, we extracted the data about the loadshapes. The input was a time series with 15 min intervals, giving the moment-by-moment electric and gas consumption. These then were transformed into a matrix with two columns, electricity and gas, with rows corresponding to time, one per hour (averaged the energy consumption). The matrix X_1 is used as input to both our models.

On the other side, we extract metadata on the building. There is one file per upgrade, one row per building. On one side we created a vector X_2 which concatenates information on `['climate_zone', 'county', 'state', 'city', 'building_type']`. This vector is also part of the inputs of the problem. We also created Y_1 which is a 42 array long, transporting the CO_2 emissions for both electric and gas uses through the year, along with the energy consumption. Lastly, we created Y_2 concatenating more extensive data about the housings: `['sqft', 'nb_bedrooms', 'nb_floors','age', 'cooling_type', 'heating_type', 'nb_windows', 'pv_size', 'electric_vehicle']`. This vector is used as labels for the classification problem.

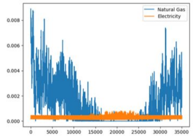

FIGURE 1. Example input data curve: timeseries data for electricity and gas.

3. Prediction Problem

We trained a two layer convolutional neural network (CNN) to process the two load curves and perform feature extraction. We flatten the output and append relevant metadata (simple information like the climate region and house type), which we then pass to a three layer feed forward neural network:

```
class CarbonReductionCNN(nn.Module):
    def __init__(self):
        super(CarbonReductionCNN, self).__init__()
        self.conv1 = nn.Conv1d(
    in_channels=2,
    out_channels=64,
    kernel_size=5
  )
        # TSet Pooling Size
        self.p = 2
        self.pool = nn.MaxPool1d(kernel_size=self.p)
        self.conv2 = nn.Conv1d(
    in_channels=64,
  out_channels=128,
  kernel_size=5
  )
        # Adjust the input size based on your data
        self.fc1 = nn.Linear(
    128 * (((n // self.p - self.p) // self.p) - self.p) +
     m, 256
  )
        self.fc2 = nn.Linear(256, 128)
        self.output_layer = nn.Linear(64, t)


    def forward(self, x1, x2):
        x = self.pool(F.relu(self.conv1(x1)))
        x = self.pool(F.relu(self.conv2(x)))
        x = torch.flatten(x, 1)
        x = F.relu(self.fc1(torch.hstack([x, x2])))
        x = F.relu(self.fc2(x))
        x = self.output_layer(x)
        return x
```

We implemented the model in PyTorch and trained using an Nvidia V100 GPU via Google Colabs Cloud Computing service.

Our model's performance was evaluated based on its ability to accurately predict the outcomes of the test data, which was not used during the training phase.

Before training, the dataset was randomly divided into a training set and a test set. The training set was used to train the model, while the test set was used to evaluate its performance. Data preprocessing steps, such as normalization and handling of missing values, were applied to ensure the quality of training, as well as task-specific issues tackled earlier in this writeup.

Recap

Accelerating building decarbonization through:

Precision targeting with minimal data…

Carbon Cut

Building greener futures

Building greener futures

Thank you!