Predicting Building Energy Usage

w207 section 3 - C. Ilin
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https://github.com/bennnyys/w207-sec3-final-proj-DMR

Motivation

What question are we working on?
Why is it interesting?

- Can we predict energy usage from building characteristics?
  - Energy use intensity - site
- Current modeling requires many inputs, lots of expensive time, specific people, and computational power
  - EnergyPlus, DOE2, eQUEST, etc.
- Reduced order modeling can more easily inform building system planning for new construction as well as retrofit decision making
- If we change one thing in a building, will it save energy?
- Target - within 20% error

Estimated “Best Features”

- year of construction
- building type
- window-wall ratio
- wall r-value
- floor r-value
- ceiling r-value
- window surface area

- climate zone
- heating type
- cooling type
- number of stories
- number of occupants
- estimated air leakage

Data

What data are we using?

- U.S. Department of Energy Building Performance Database
  - Energy consumption and building characteristics of actual buildings from 16 states/municipalities in the U.S. (New York, San Francisco, Chicago, D.C., Seattle, Philadelphia, Austin, etc.)
- Up to 10 years of panel data per building
- Number of rows: 296,065
- Number of features: 33
- Main features
  - Site EUI (energy use intensity: kBtu per square feet, 91k NaN)
    - Also: year, electric EUI (95k NaN), fuel EUI (135k NaN), GHG emissions (152k NaN)
  - Climate region (combination of temperature and humidity, 823 NaN)
  - Residential or Commercial (0 NaN)
  - Facility type (office, education, warehouse, industrial, lodging, etc., 156k NaN)
  - Floor Area (square feet, 0 NaN)
  - Year built (4,779 NaN)
  - Energy star rating (206k NaN)

State/Municipality Dataset Analysis

- Austin - 8,390 (~1,600 rows with roof/ceiling and window glass data)
- Berkeley - 414
- Boston - 6,835 (~4,500 rows with energy star ratings)
- CA Building Energy Benchmarking Program - 3,881
- CA Prop 39 K-12 Program - 1,501
- Cambridge - 4,122
- Chicago - 11,937
- Fannie Mae - 857
- Gainesville - 154,528 (includes cooling, roof_ceiling type, but only 75k with site_eui)
- NYC Ordinance - 54,298
- NY Residential - 439
- Philadelphia - 6,457
- San Francisco - 9,647
- Seattle - 17,002
- Syracuse - 139
- D.C. - 15,618

Fairness

- Location skew - data collected at state/municipal level mostly large coastal cities
- Income skew - buildings which receive energy audits may be skewed to affluent communities
  - Health and safety usually prioritized over energy efficiency in less affluent communities
- Consistency - Commercial vs Residential
  - Commercial buildings have significant variation in construction compared to residential buildings

Descriptive Statistics: numeric

	year	floor_area	year_built	energy_star_rating	electric_eui	fuel_eui	site_eui	source_eui	ghg_emissions_int
count	296065.000000	2.960650e+05	291286.000000	89543.000000	200966.000000	160800.000000	204210.000000	196936.000000	143854.000000
mean	2013.978505	7.469098e+04	1971.887276	61.809511	29.602798	23.291331	63.231037	126.836547	4.937401
std	2.609692	1.796745e+05	28.742165	28.910037	28.690731	32.060086	54.413696	110.338840	4.202703
min	2010.000000	5.000000e+02	1649.000000	0.000000	0.000000	0.000000	1.001169	1.075772	0.000000
25%	2012.000000	1.635000e+03	1961.000000	40.000000	16.253904	8.182419	32.009412	72.190118	2.881654
50%	2014.000000	3.260000e+03	1978.000000	68.000000	23.384545	15.138294	50.051977	102.748173	4.026421
75%	2016.000000	8.036400e+04	1993.000000	86.000000	33.968446	26.041885	79.382514	146.732770	5.665176
max	2020.000000	6.385382e+06	2020.000000	100.000000	987.466930	936.379589	997.866120	3133.315574	109.708218

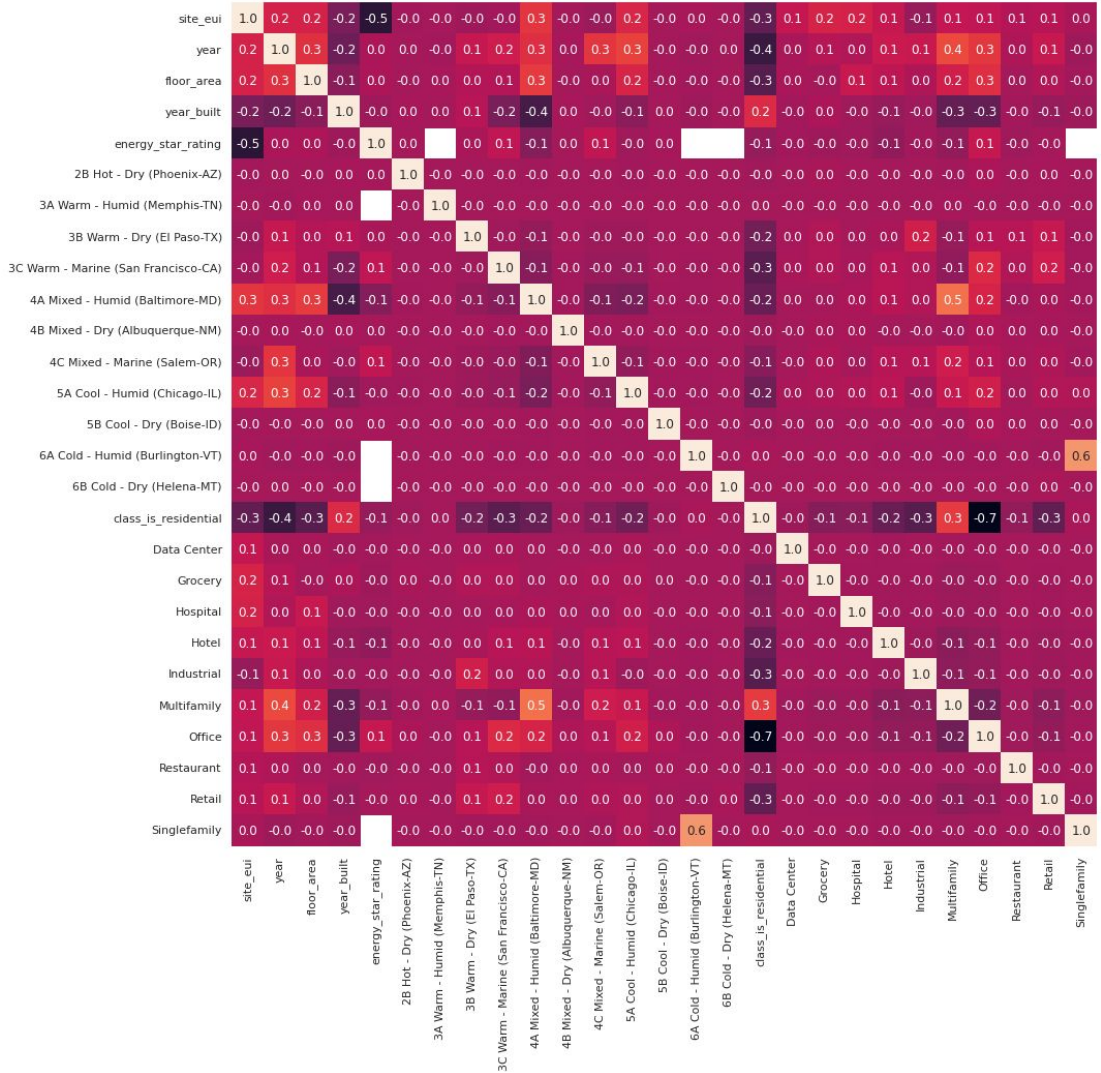
Descriptive Statistics: categorical

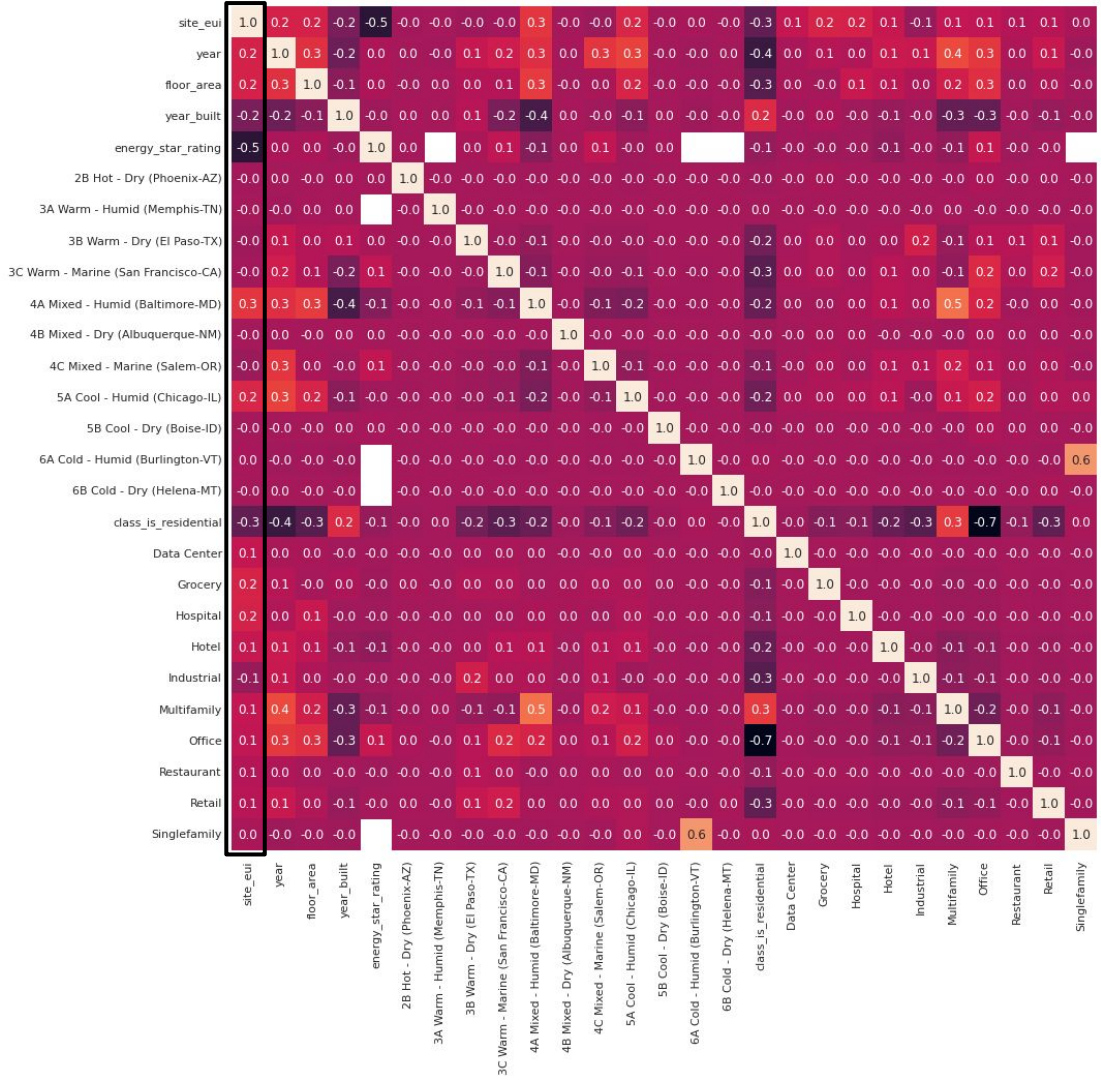
```
 CLIMATE - number of distinct vals: 12 ----------
2A Hot - Humid (Houston-TX)            162918
4A Mixed - Humid (Baltimore-MD)         76484
5A Cool - Humid (Chicago-IL)            23269
4C Mixed - Marine (Salem-OR)            17039
3C Warm - Marine (San Francisco-CA)     11171
3B Warm - Dry (El Paso-TX)               3957
NaN                                       823
6A Cold - Humid (Burlington-VT)           183
4B Mixed - Dry (Albuquerque-NM)            95
5B Cool - Dry (Boise-ID)                   67
Name: climate, dtype: int64

 BUILDING_CLASS - number of distinct vals: 2 -----
Residential    223601
Commercial      72464
Name: building_class, dtype: int64
```

```
 FACILITY_TYPE - number of distinct vals: 82 ------
NaN                                   156941
Multifamily - Uncategorized            56268
Office - Uncategorized                 22030
Education - Other classroom             8350
2-4 Unit Building                       5018
5+ Unit Building                        4508
Lodging - Hotel                         4327
Retail - Uncategorized                  3362
Education - College or university       3118
Commercial - Other                      2586
Name: facility_type, dtype: int64
```

Descriptive Statistics: correlation matrix

- Most promising features
  - Features with low NaN counts
  - Turn categorical features into multi-hot
  - Calculate correlation between features


site_eui
year
floor_area
year_built
energy_star_rating
2B Hot - Dry (Phoenix-AZ)
3A Warm - Humid (Memphis-TN)
3B Warm - Dry (El Paso-TX)
3C Warm - Marine (San Francisco-CA)
4A Mixed - Humid (Baltimore-MD)
4B Mixed - Dry (Albuquerque-NM)
4C Mixed - Marine (Salem-OR)
5A Cool - Humid (Chicago-IL)
5B Cool - Dry (Boise-ID)
6A Cold - Humid (Burlington-VT)
6B Cold - Dry (Helena-MT)
class_is_residential
Data Center
Grocery
Hospital
Hotel
Industrial
Multifamily
Office
Restaurant
Retail
Singlefamily


site_eui
year
floor_area
year_built
energy_star_rating
2B Hot - Dry (Phoenix-AZ)
3A Warm - Humid (Memphis-TN)
3B Warm - Dry (El Paso-TX)
3C Warm - Marine (San Francisco-CA)
4A Mixed - Humid (Baltimore-MD)
4B Mixed - Dry (Albuquerque-NM)
4C Mixed - Marine (Salem-OR)
5A Cool - Humid (Chicago-IL)
5B Cool - Dry (Boise-ID)
6A Cold - Humid (Burlington-VT)
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class_is_residential
Data Center
Grocery
Hospital
Hotel
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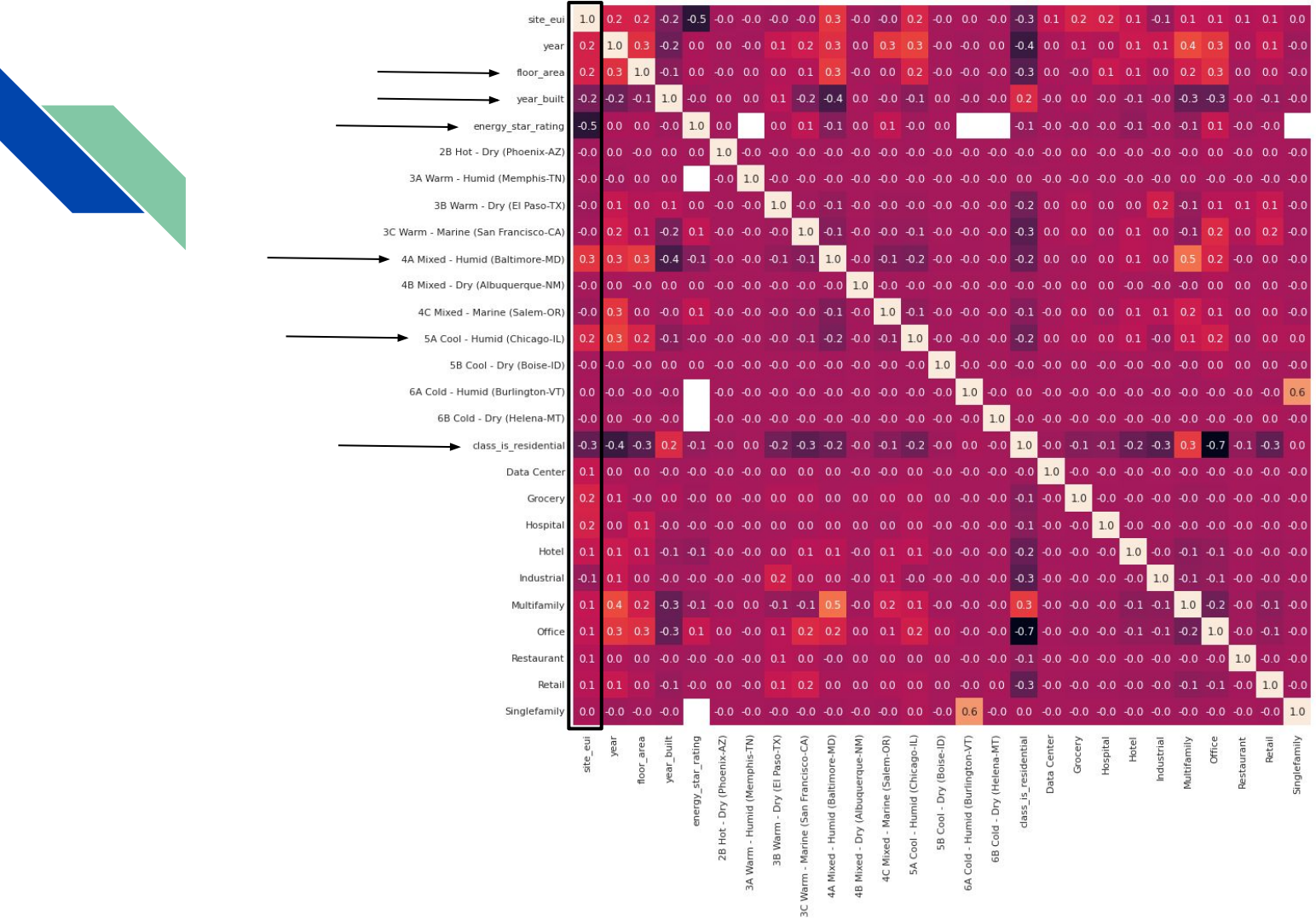

site_eui
year
floor_area
year_built
energy_star_rating
2B Hot - Dry (Phoenix-AZ)
3A Warm - Humid (Memphis-TN)
3B Warm - Dry (El Paso-TX)
3C Warm - Marine (San Francisco-CA)
4A Mixed - Humid (Baltimore-MD)
4B Mixed - Dry (Albuquerque-NM)
4C Mixed - Marine (Salem-OR)
5A Cool - Humid (Chicago-IL)
5B Cool - Dry (Boise-ID)
6A Cold - Humid (Burlington-VT)
6B Cold - Dry (Helena-MT)
class_is_residential
Data Center
Grocery
Hospital
Hotel
Industrial
Multifamily
Office
Restaurant
Retail
Singlefamily

Experiments

Prediction Algorithm

Linear Regression

- The feature we are trying to predict is a continuous, numerical variable which makes it a good candidate for predicting with a linear model.

Random Forest

- A random forest regression may be best able to handle the number of categorical and missing variables.

Feed Forward Neural Network

- Tried to improve on our initial linear model by building a feed forward neural network to try and achieve any possible marginal gains.

How will we evaluate our results?

- We chose to use Mean Absolute Error (MAE) as our evaluation metric.
- It is easy to interpret since it tells us how many energy intensity units our predictions were off by.
- MAE is less sensitive to outliers than Mean Squared Error and our data have observations with site EUI values multiple standard deviations above the mean.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right|$$

Baseline Model

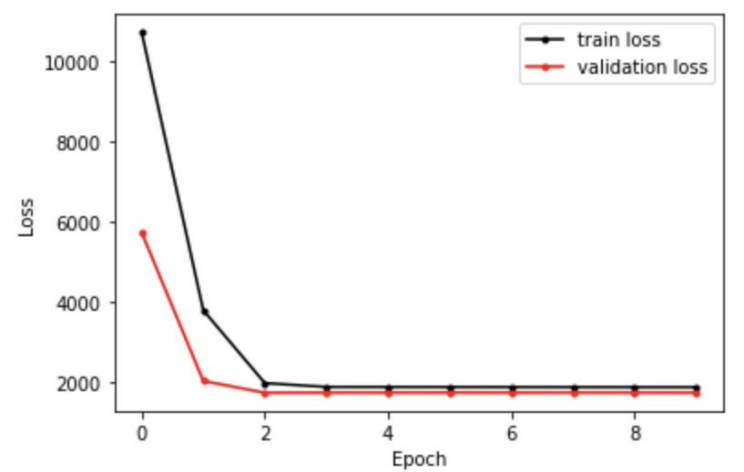
MSE and MAE from the mean

```
MSE Baseline to Train:  1563.4135692561551
MSE Baseline to Test:  1349.2001965901652
```

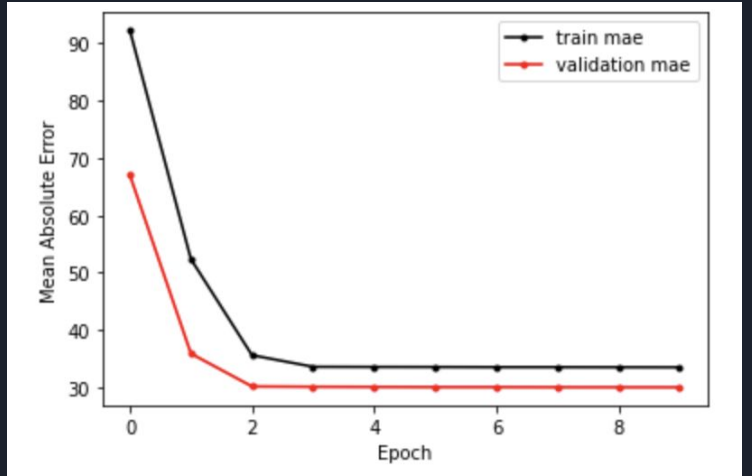
```
MAE Baseline to Train:  29.96627005205943
MAE Baseline to Test:  28.480106853244518
```

Experiments: Linear Regression

Baseline Linear Model - Year Built

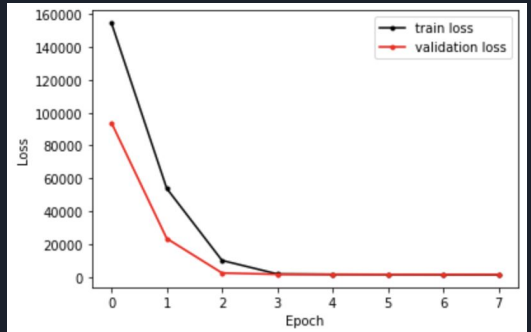



```
Final train loss: 1862.2264404296875
Final validation loss: 1724.9371337890625
```

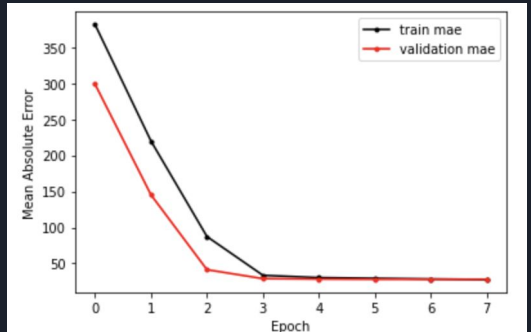



```
Final train mae: 33.49901580810547
Final validation mae: 30.01226043701172
```

Linear Model - Full Feature




```
Final train loss: 1412.6356201171875
Final validation loss: 1533.863037109375
```

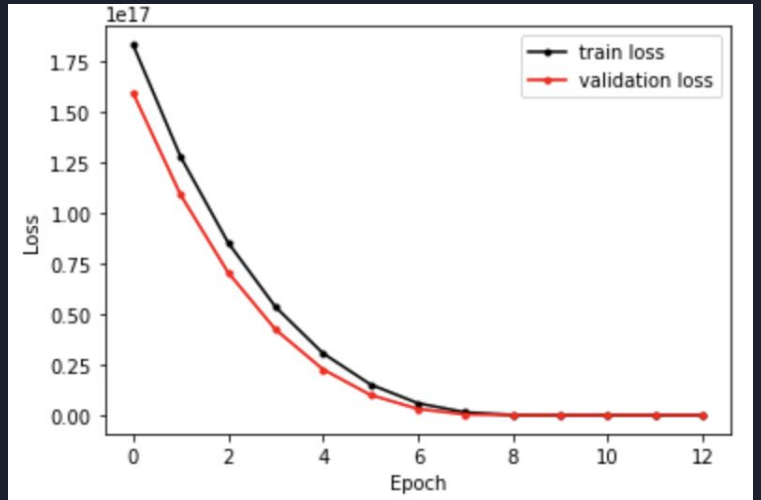



```
Final train mae: 27.731264114379883
Final validation mae: 27.989164352416992
```

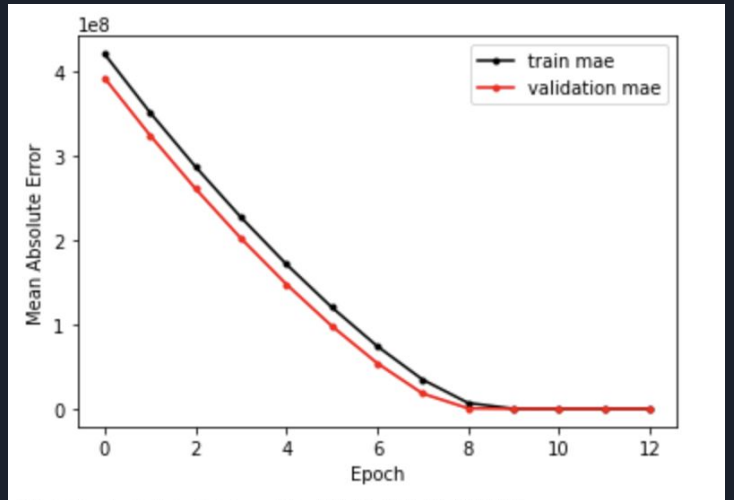
Features include:

- Floor area
- Year of construction
- Year of data collection
- Climate zone - one hot
- Building type - one hot
- Window glass layers - one hot
- Roof type - one hot
- Cooling type - one hot
- Heating type - one hot
- Wall type - one hot

Normalized Baseline Linear Model - Year Built

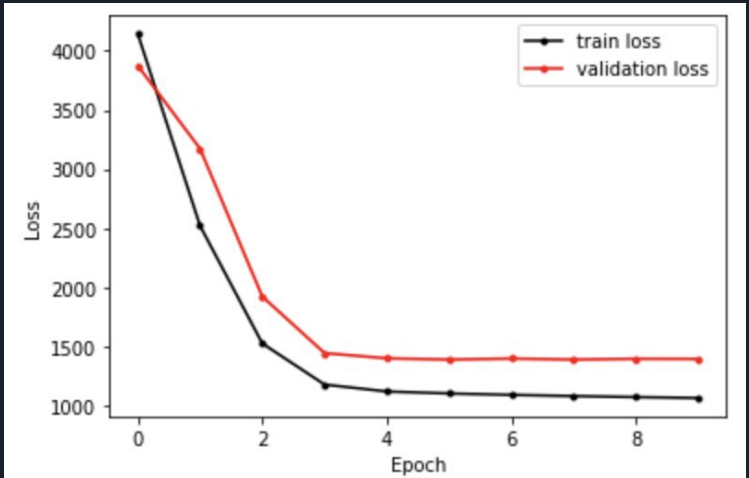


Final train loss: 1736.6119384765625
Final validation loss: 1636.8787841796875

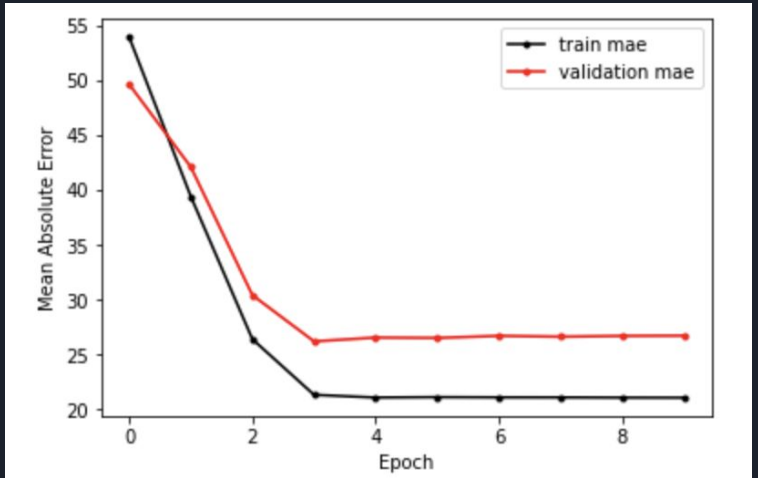


Final train mae: 31.90424919128418
Final validation mae: 28.7767276763916

Normalized Linear Model - Full Feature



Final train loss: 1062.92724609375
Final validation loss: 1393.57666015625

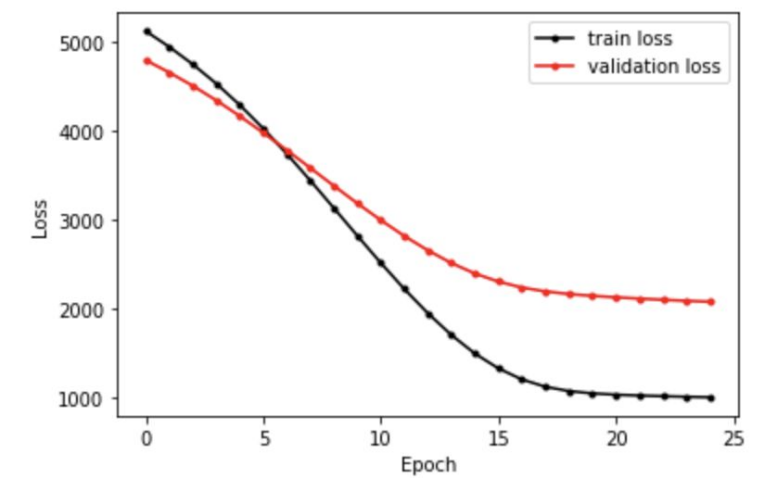


Final train mae: 21.0861759185791
Final validation mae: 26.736709594726562

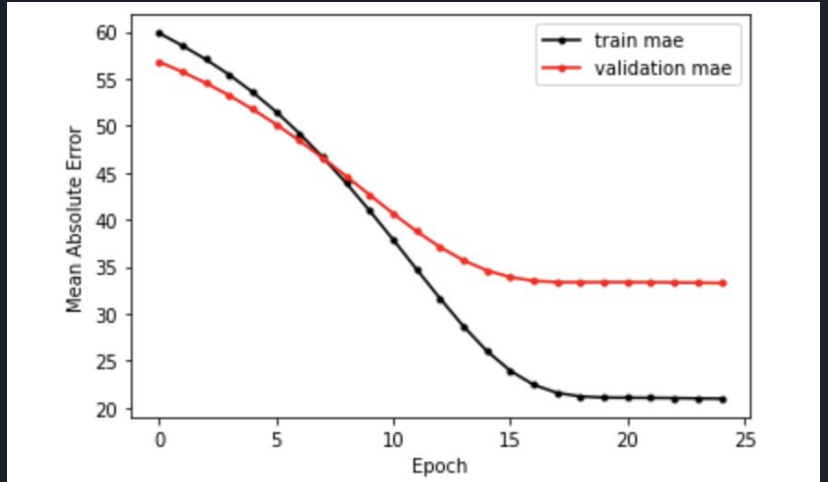
Deep Neural Network Regression

- Normalization layer
- Dense non-linear layer with ReLU activation
- Dense linear single-output layer

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 55)               111
 n)

 dense_2 (Dense)             (None, 64)                3584

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 3,760
Trainable params: 3,649
Non-trainable params: 111
_________________________________________________________________
```




```
Final train loss: 1000.8352661132812
Final validation loss: 2075.447509765625
```




```
Final train mae: 20.94822120666504
Final validation mae: 33.24668502807617
```

Best Linear Model (Normalized Full-Feature) Weights

```
Final bias: 6.33
year 222.7343
floor_area 127.4397
year_built 175.1638
clim_2A Hot - Humid 0.3617
clim_3C Warm - Marine 0.0001
clim_5A Cool - Humid 0.0
clim_3B Warm - Dry 0.0184
clim_2B Hot - Dry 0.0415
clim_4C Mixed - Marine 0.361
clim_6B Cold - Dry 0.0002
clim_4B Mixed - Dry 0.0893
clim_5B Cool - Dry 0.1233
clim_4A Mixed - Humid 0.0
clim_6A Cold - Humid 0.0011
clim_3A Warm - Humid 0.0
BC_Residential 0.314
BC_Commercial 0.686
FT_Multifamily 0.0003
FT_Industrial 0.0073
FT_Office 0.0056
FT_Retail 0.0442
FT_Other 0.036
FT_Hotel 0.3233
FT_Restaurant 0.1804
FT_Grocery 0.0113
FT_Hospital 0.0024
FT_Data Center 0.037
FT_Singlefamily 0.0027
```

```
WGL_Single-pane 0.0012
WGL_Double-pane 0.0058
WGT_Low-e 0.0002
roof_Shingles 0.3233
roof_Built-up 0.0168
roof_Slate or tile shingles 0.0
roof_Metal surfacing 0.0023
roof_Other Or Combination 0.0031
roof_Asphalt/fiberglass/other shingles 0.0002
roof_Wood shingles/shakes/other wood 0.0071
roof_Plastic/rubber/synthetic sheeting 0.0006
roof_Green Roof 0.0
cool_Central AC 0.3305
cool_No cooling 0.0
cool_Other 0.0102
cool_Cooling_Heat Pump 0.0
cool_Split AC 0.0
heat_Boiler 0.0002
heat_Resistance Heating 0.0
heat_Heating_Heat pump 0.0
heat_Other 0.0
heat_Heating_Furnace 0.0
wall_Other 0.0013
wall_wall_Wood 0.0004
wall_wall_Metal 0.0
wall_wall_Brick_stone 0.0003
wall_wall_Concrete 0.0007
```

Linear Model Results - Test Set

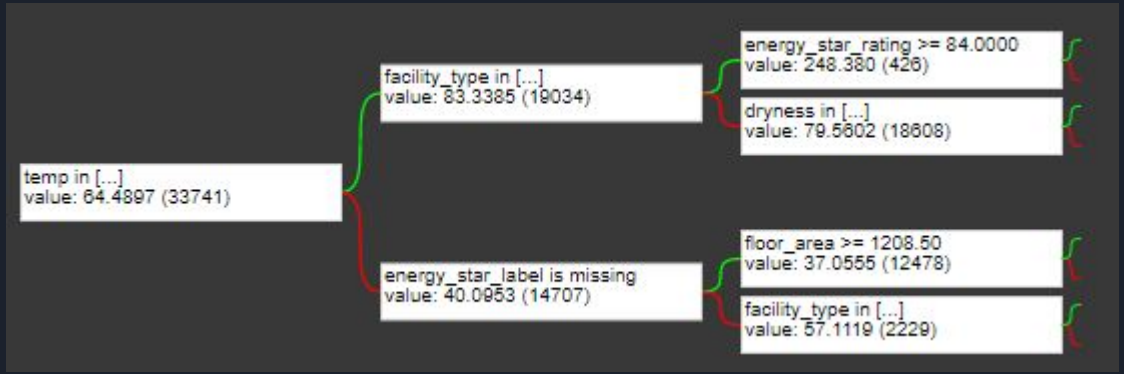
Full featured normalized model has best performance and had most ideal loss plot

	Year_Built	Full_Feature	Year_Built_Norm	Full_Feature_Norm	DNN_Model
MSE	1617.91	1175.92	1477.95	803.35	965.60
MAE	31.59	25.49	29.90	19.12	20.75

Experiments: Random Forest

Random Forest Model

- Features:
  - Facility type, floor area, year_built, roof/ceiling, window glass layers, window glass type, energy star label and rating, cooling ,heating, residential, dryness, temperature
- Data cleaning:
  - Drop rows without site EUI
  - Drop duplicate rows for same building (keep most recent)
  - Train: 34k, Validation: 8k, Test: 19k



Random Forest

Model:

```
# Specify the model.
model = tfdf.keras.RandomForestModel(
    task = tfdf.keras.Task.REGRESSION,
    temp_directory= path + 'output_ben/',
    verbose = 2,
    allow_na_conditions=True,
    max_depth=25,
    min_examples=3,
    num_trees=300,
    random_seed=3000,
    name='Random_Forest_Regressor',
    )
```

Train:

```
mse: 540.2357
mae: 10.4744
mape: 32.1941
RMSE: 23.24297004985123
```

Test:

```
mse: 1218.7836
mae: 16.1808
mape: 47.1652
RMSE: 34.9110808961272
```

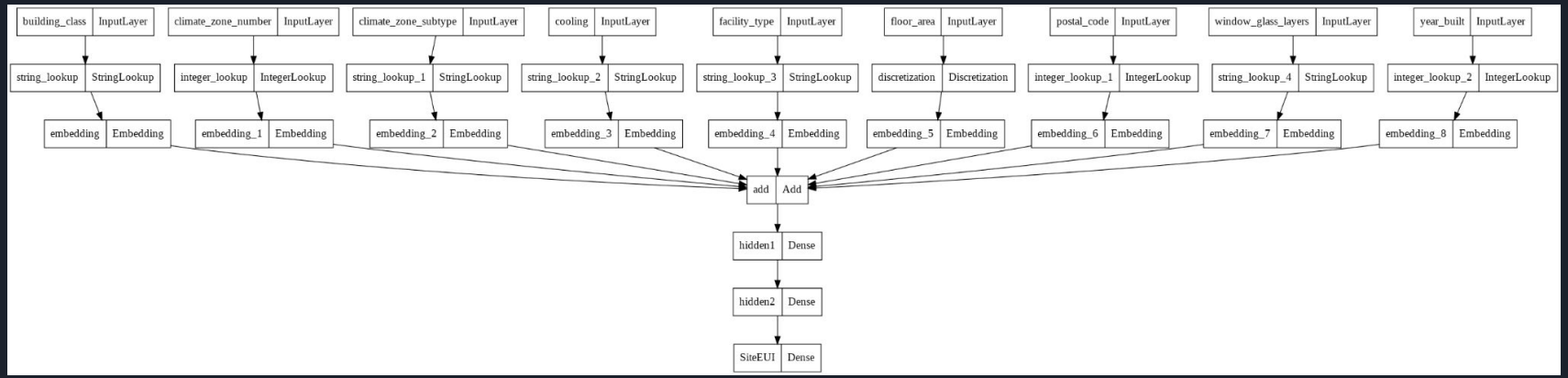
Experiments: Feed Forward Neural Network

FFNN

- Extract climate zone number and subtype as individual features
- Convert all features to embeddings
- Use Tensorflow Functional API with a simple model architecture of 2 fully connected layers with 32 nodes each.
- Exponential decay learning rate schedule

```
# Tensorflow input layers
building_class = tf.keras.layers.Input(shape=(1,), dtype=tf.string, name='building_class')
climate_zone_number = tf.keras.layers.Input(shape=(1,), dtype=tf.int64, name='climate_zone_number')
climate_zone_subtype = tf.keras.layers.Input(shape=(1,), dtype=tf.string, name='climate_zone_subtype')
cooling = tf.keras.layers.Input(shape=(1,), dtype=tf.string, name='cooling')
facility_type = tf.keras.layers.Input(shape=(1,), dtype=tf.string, name='facility_type')
floor_area = tf.keras.layers.Input(shape=(1,), dtype=tf.int64, name='floor_area')
postal_code = tf.keras.layers.Input(shape=(1,), dtype=tf.int64, name='postal_code')
window_glass_layers = tf.keras.layers.Input(shape=(1,), dtype=tf.string, name='window_glass_layers')
year_built = tf.keras.layers.Input(shape=(1,), dtype=tf.int64, name='year_built')

# Tensorflow categorical feature layers
building_class_binned = tf.keras.layers.StringLookup(vocabulary=['Commercial', 'Residential'])(building_class)
climate_zone_number_binned = tf.keras.layers.IntegerLookup(vocabulary=[2, 3, 4, 5, 6])(climate_zone_number)
climate_zone_subtype_binned = tf.keras.layers.StringLookup(vocabulary=['A', 'B', 'C'])(climate_zone_subtype)

cooling_vocab = get_feature_vocab(df_train.cooling)
cooling_binned = tf.keras.layers.StringLookup(vocabulary=cooling_vocab)(cooling)

facility_type_vocab = get_feature_vocab(df_train.facility_type)
facility_type_binned = tf.keras.layers.StringLookup(vocabulary=facility_type_vocab)(facility_type)

floor_area_bins = list(np.percentile(df_train_int["floor_area"],[10,20,30,40,50,50,70,80,90]))
floor_area_binned = tf.keras.layers.Discretization(bin_boundaries=floor_area_bins)(floor_area)

postal_code_vocab = get_feature_vocab(df_train.postal_code)
postal_code_binned = tf.keras.layers.IntegerLookup(vocabulary=postal_code_vocab)(postal_code)

window_glass_layers_binned = tf.keras.layers.StringLookup(vocabulary=['Single-pane', 'Double-pane'])(window_glass_layers)

year_built_vocab = get_feature_vocab(df_train.year_built)
year_built_binned = tf.keras.layers.IntegerLookup(vocabulary=year_built_vocab)(year_built)

# Tensorflow embedding layers
building_class_embed = tf.keras.layers.Embedding(
    input_dim = 3, output_dim = embed_dim, input_length = 1)(building_class_binned)
climate_zone_number_embed = tf.keras.layers.Embedding(
    input_dim = 6, output_dim = embed_dim, input_length = 1)(climate_zone_number_binned)
climate_zone_subtype_embed = tf.keras.layers.Embedding(
    input_dim = 4, output_dim = embed_dim, input_length = 1)(climate_zone_subtype_binned)
cooling_embed = tf.keras.layers.Embedding(
    input_dim = len(cooling_vocab) + 1, output_dim = embed_dim, input_length = 1)(cooling_binned)
facility_type_embed = tf.keras.layers.Embedding(
    input_dim = len(facility_type_vocab) + 1 , output_dim = embed_dim, input_length = 1)(facility_type_binned)
floor_area_embed = tf.keras.layers.Embedding(
    input_dim = len(floor_area_bins)+1, output_dim = embed_dim, input_length = 1)(floor_area_binned)
postal_code_embed = tf.keras.layers.Embedding(
    input_dim = len(postal_code_vocab)+1, output_dim = embed_dim, input_length = 1)(postal_code_binned)
window_glass_layers_embed = tf.keras.layers.Embedding(
    input_dim = 3, output_dim = embed_dim, input_length = 1)(window_glass_layers_binned)
year_built_embed = tf.keras.layers.Embedding(
    input_dim = len(year_built_vocab) + 1, output_dim = embed_dim, input_length = 1)(year_built_binned)
```

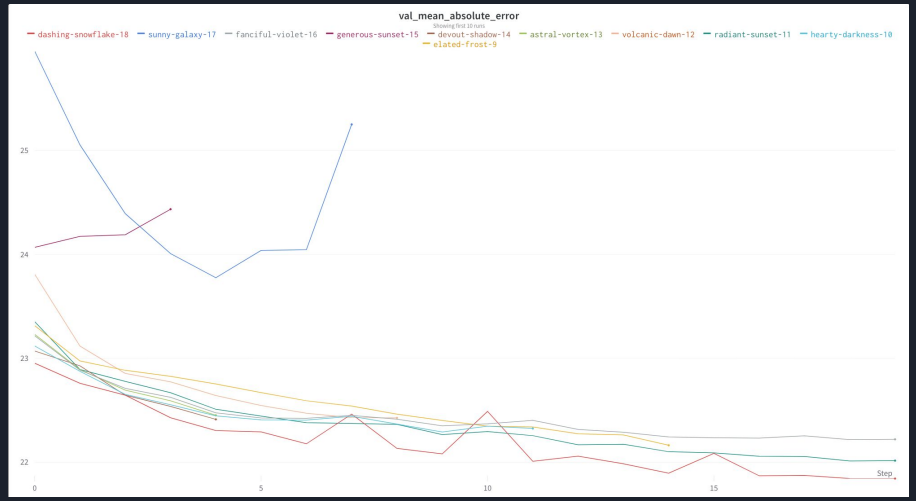
FFNN

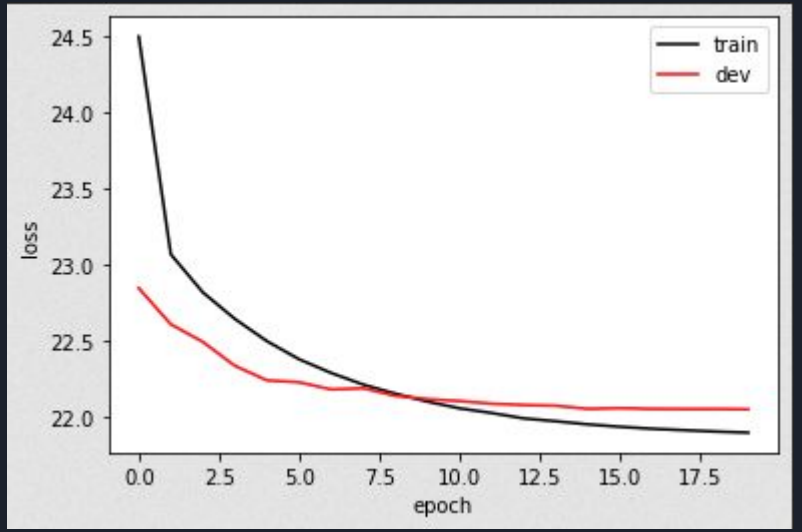

building_class InputLayer
climate_zone_number InputLayer
climate_zone_subtype InputLayer
cooling InputLayer
facility_type InputLayer
floor_area InputLayer
postal_code InputLayer
window_glass_layers InputLayer
year_built InputLayer
string_lookup StringLookup
integer_lookup IntegerLookup
string_lookup_1 StringLookup
string_lookup_2 StringLookup
string_lookup_3 StringLookup
discretization Discretization
integer_lookup_1 IntegerLookup
string_lookup_4 StringLookup
integer_lookup_2 IntegerLookup
embedding Embedding
embedding_1 Embedding
embedding_2 Embedding
embedding_3 Embedding
embedding_4 Embedding
embedding_5 Embedding
embedding_6 Embedding
embedding_7 Embedding
embedding_8 Embedding
add Add
hidden1 Dense
hidden2 Dense
SiteEUI Dense

FFNN

It proved to be very difficult to beat the performance of the full-feature, normalized linear regression model

Extensive experimentation and hyperparameter tuning could not return a MAE below 21.





Conclusions

Conclusions

- More and better data is needed
- Need more representative buildings from the communities this model will be used in
- Residential and commercial buildings should potentially be separately modeled to reduce complexity and more effectively select features

Code and Contributions

Code and Contributions

Code

- GitHub Repo: https://github.com/bennnyys/w207-sec3-final-proj-DMR

	Ben	Sam	CJ
Theoretical Research		X	
Data cleaning	X	X	X
Data splitting	X		
Hyperparameter tuning	X	X	X
Augmentations	(random forest)	(linear regression)	(FFNN)
Presentation Slides	X	X	X