NFIRS Property Loss Prediction Model

Machine Learning Engineer Nanodegree

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I. Firefighting and property damage

Overview

The National Fire Incident Reporting System (NFIRS) is both a data set and a series of software systems built around collecting data on fires in the US and analyzing it for many purposes (national initiative effectiveness, risk management, etc). It was established by the USFA (United States Fire Administration) and is freely available to the public. Many firefighting agencies in the United States provide data on each incident they respond to into this national system.

I personally have worked with NFIRS before on the reporting side; as a firefighter and later an officer in the Boone County Fire Protection District, all of the reports I wrote and some of the ad-hoc software I implemented interfaced with the ingestion end of the NFIRS database. Some of the interesting information available in it is a series of categorization fields for each incident and the total resulting property damage.

This loss data is of particular interest because when prioritizing incidents and when doing incident preplanning, having comparative predictions of actual likely property loss for a given structure or residence and incident type could be very valuable to a dispatch center, insurance agency, or first due fire officer for a response area.

Example Use Cases for a predictive property loss algorithm:

- During a large natural disaster when many fires are reported simultaneously in real time, a dispatch agency may choose to prioritize response to incidents (or proactively increase the default response level to a given incident) based upon predicted property damages.
- When performing a risk analysis, an insurance agent may wish to augment their actuarial tables with predictive property loss for this particular structure given a range of potential incidents, thus more finely calibrating the premium to charge for a given range of coverage.

- Officers at a fire station often choose which structures in their runbox to do detailed preplanning on based on perceived risk. Having predicted property loss for a range of structures could help inform priority decisions for the most important structures to perform detailed planning exercises for.

For this project I will be using just the NFIRS data from 2011 (which is still a very large dataset), but in a production system this dataset would benefit from being continually adjusted for inflation and augmented in an ongoing manner with additional data from each year as data is added to the NFIRS database.

Intended Approach

For this project I will be taking the raw dbase files for the 2011 NFIRS data. The dataset is very big (2.2 million basic records) and we don't actually need all of it as some of those incidents are not fires (Medical, hazmat, search and rescue, etc).

I intend to reduce the set of data under consideration to just structural fire incidents, and extract/normalize just the features that are relevant to predicting property loss. Then I intend to use the sklearn framework to train a regression model such that given a set of features for a target structure/incident, we can make a reasonable prediction of likely real property loss.

Possible Example Usecase: A dispatch center receives a 911 call reporting a single-room fire inside a residential single-family dwelling at a given address.
That address is used by supporting software systems to query dimensions of the structure. Questions from the dispatcher are used to establish what materials are on site and what the expected ignition source was, whether a fire detector has sounded, etc (standard questions currently asked in 911 calls during dispatch).
The data is fed into the model and produces an expected dollar value of $237,500.00 property loss from this incident. Based on the unexpectedly high property loss estimate, a second alarm (extra fire trucks and personnel) are immediately dispatched rather than waiting for the first engine to arrive and size up the scene.

Cost function and Validation

To train the algorithm, I'll be using a couple different metrics for evaluating the accuracy of the model.

First is Mean Squared Error; in layman's terms, this is taking the sum of the squared differences between each real y value and the predicted y value for the current function, divided by the number of elements (the average of the squared error in prediction). This is formally written as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$$

This is useful because it's always positive (due to squaring the difference), but it does penalize outliers pretty heavily. Also it's difficult to intuitively link to the target variable because it's in squared units. That's why we'll also be looking at the Root of Mean Squared Error. This is simply the square root of MSE, which transforms the metric into the same units as the variable being examined.

I'll also be using R-Squared, or as some formal texts call it the "Coefficient of determination". In layman's terms this is often described by saying "this represents how much of the variation is attributable to the input variable". It is calculated by dividing the residual sum of squares by the total sum of squares and subtracting this quantity from one:

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=0}^{n_{\text{samples}}-1}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n_{\text{samples}}-1}(y_i - \bar{y})^2}$$

Naturally this means that if the model predicts every point perfectly, then it will have an r-squared value of 1.0. Generally 0 is the lower bound when evaluating a regression against the points that were regressed, but in cases like machine learning where we're scoring it against data it has not seen yet, it's possible for r-squared to be arbitrarily bad (and therefore negative).

r-squared is a little easier to digest because of the generally bounded range, but RMSE is in the units under consideration and is easier to have an intuitive feel of magnitude of error. Both metrics can be useful for evaluating a model.

II. Analysis

Data Exploration

Before we dive in to the data itself, a note on it's origins. I obtained only data for 2011 because it's provided free of paperwork from NFIRS for being able to start playing with basic models and understanding the format. It is possible to request their entire dataset, but this involves some simple authorization and paperwork which seemed an obstacle to getting started on the modeling stage. The gains that I would have in model accuracy from having the additional data from all

years is discussed in the "Improvements" section at the end of this report.

The NFIRS data arrives in a set of tables that can be joined together. The "basicincident.dbf" file has fields that apply to all incidents, and then there are other incident fields which are different per type of incident being described (basicaid, arson, fireincident, hazmat, wildlands, etc). For the purposes of this analysis, we're looking at fire incidents and the property loss they cause, so we really only need the basicincident.dbf file and the fireincident.dbf file.

There are over 2 million records in the basicincident file, but only about 600k have a record in the fireincident table. We'll further select out those incidents which result in no damage (there are many) and those that are not of a "fire" incident type (even in fire incidents, there are things like false alarms which are common), so our final data set is actually closer to 200k records.

The target column we'll be looking at is "PROP_LOSS", which represents the dollar value loss of property destroyed in a given emergency incident. After trimming outliers (there are several high-dollar value losses that really skew the data over all), here's what the distribution looks like:

```
| stat  | PROP_LOSS $ value |
| count |  196574.000000    |
| mean  |    8914.580748    |
| std   |   12933.652034    |
| min   |       1.000000    |
| 25%   |    1000.000000    |
| 50%   |    3000.000000    |
| 75%   |   10000.000000    |
| max   |   60000.000000    |
```

We can see that even after chopping off a lot of high value outliers, the data skews heavily to the low end, with the median being $3000 even though the mean damage is up at $8914.

After combing the fire and basic incident tables into one tabular dataset, there are still > 130 columns to consider, many of which are not strongly related to the output target (property loss).

Most of the fields are categorical (the type of building, the type of fire, the type of ignition source, etc), but there are a few numeric fields (number of firetrucks, number of response personnel, square feet of structure).

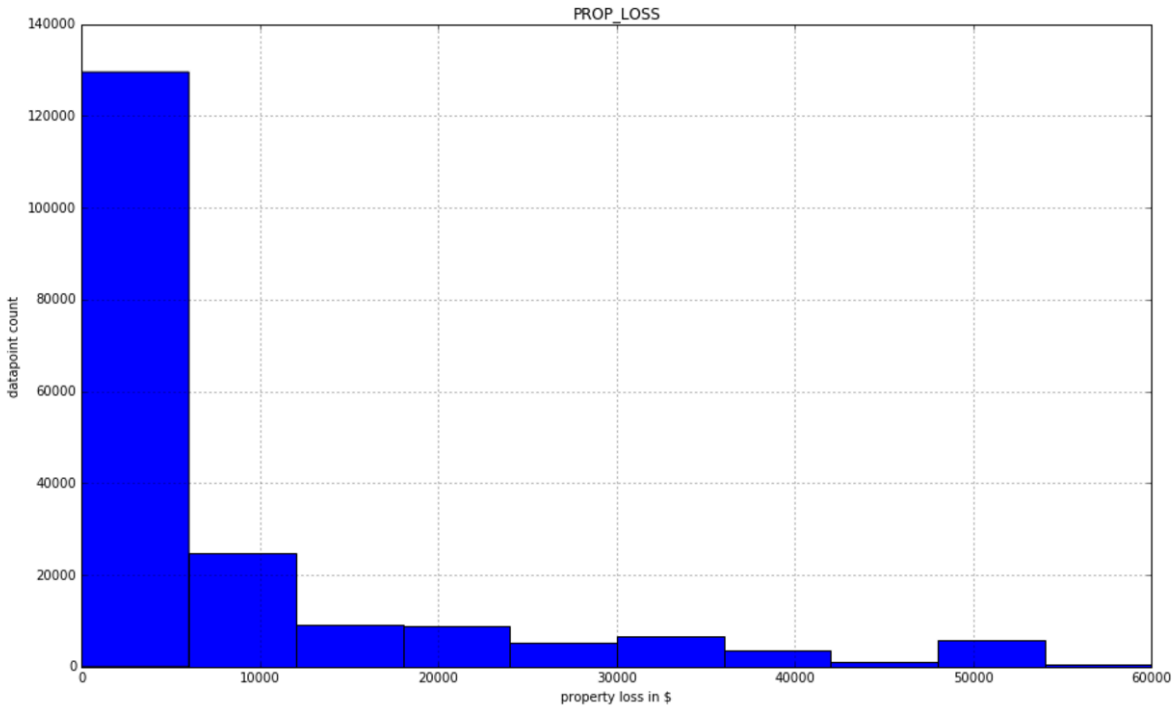
One of the challenges we have for the numeric fields is that there's plenty of missing data. For example, square feet. All buildings on fire have some square footage, but not all incident reports include it. Out of nearly 200000 records 106645 have no square foot value included. The rest are distributed like this:

field	SQ_FEET
count	87153
mean	10291
std	579840
min	1
25%	800
50%	1200
75%	1944
max	10000000

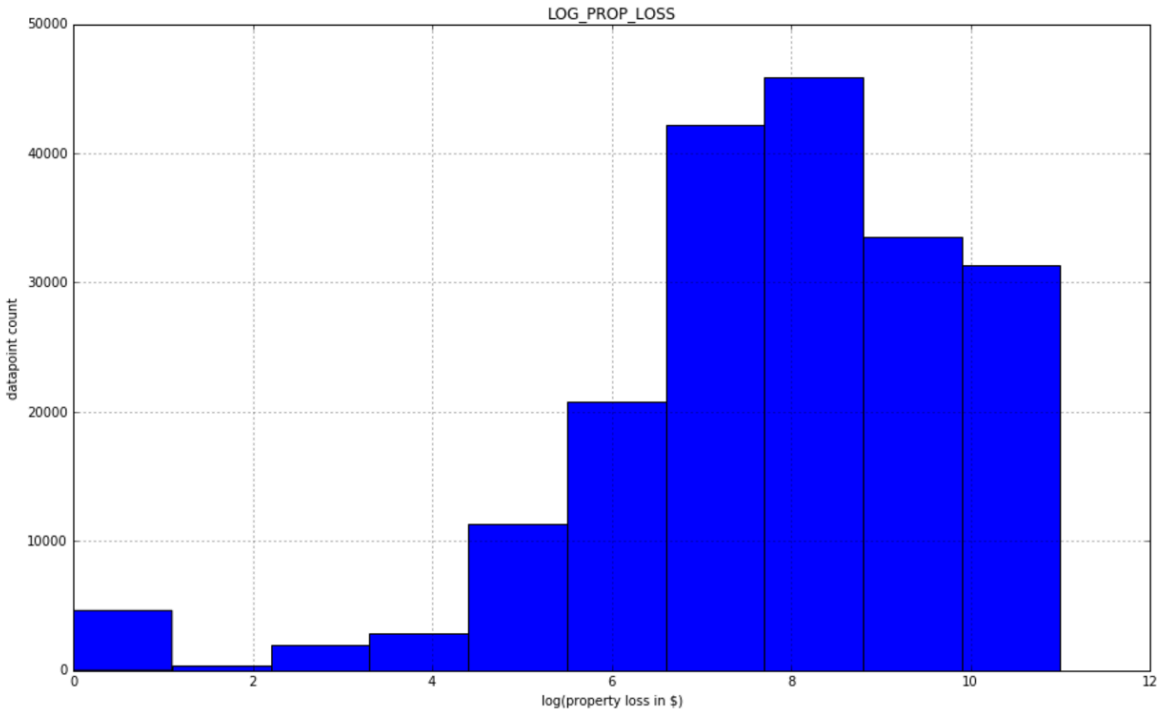
There are several fields like this, with high outliers and skewed distributions, and a lot of missing data. The plan for these numeric fields is to replace missing values with the median value of the dataset to keep a lot of 0s and -1s from throwing off the relationship, and trimming extreme outliers.

Exploratory Visualization

One of the first things I wanted to look at was the distribution of the target variable (the property loss value), because many of the values tended low and I know for regression problems it's nice to have a normal distribution. Here's the distribution of the raw data:



It skews to the right pretty significantly. I experimented with trying to perform a regression on it with several learners, and when I compared them to running the same regression exercise on the log of that target variable the difference in r-squared scores was a full 0.1 for nearly every learner in favor of the log version. Here's the same data run through a logarithmic transform first:



Algorithms and Techniques

My plan of attack was to spot check a series of regression learning algorithms and pick a few that perform fairly well with naive parameters to tune further.

The algorithm that performed above and beyond the other regressions considered was Gradient Tree Boosting. This is a process where a sequence of weak learners are fit in sequence to try to get closer and closer to the correct labels for given inputs. The set of learners are combined additively so that a prediction is really the sum of all the weak trees in the model. The "gradient" portion is for gradient descent, which in this case is by following a given loss function and trying to minimize it with each step (I use "least squares" in this project).

This algorithm has several hyper-parameters that I tuned:

loss function: Although I chose to use least squares, it's also possible to use absolute error or a couple other options that are more resilient to outliers. In this case I removed the significant

outliers from the dataset up front, and my exhaustive grid search yielded the best results with least squares.

learning_rate: this represents how much one trusts the change of each additional weak learner. However, since I tuned with the n_estimators parameter I didn't mess with this much (a lower learning rate with more learners should behave similarly to a higher learning rate with fewer learners).

n_estimators: This is just the number of boosting steps to go through, could also be though of as the number of weak learners used in sequence.

max_depth: how deep any given weak learner can go, which can help avoid overfitting.

min_samples_split: how big a leaf in a given tree is allowed to be.

For initial training I just used a series of default parameters to see how the model did out of the box, then during tuning I built a grid of possible parameter combinations and ran them exhaustively through all combinations to see which combination yielded the best performing learner.

Benchmark

I used a random dummy regression to produce a baseline set of scoring metrics in order to make sure that any results I obtained were significant. When run over the training set of data and then predicting against the test set, the Dummy learner performed as follows:

```
Mean Absolute Error:   1.56
Mean Squared Error:    4.44
RMSE:                  2.11
Median Absolute Error: 1.39
R - Squared:          -3.33
```

remember, those are errors off of the log of the property damage target. I then also checked the performance of a naive linear regression just to have a sense of how much better a given approach would do compared to the results of a fairly simply out-of-the-box algorithm using the same approach as the dummy (train against the training set, score against the test set):

```
Mean Absolute Error:   1.22
Mean Squared Error:    2.90
RMSE:                  1.70
Median Absolute Error: 0.94
R - Squared:           0.35
```

The results here are covered in detail in the AlgorithmExploration notebook.

Since the use cases described in the project plan are based upon prioritization between records more than precision, I have another benchmark in mind for testing the model. I expect that for any random set of 2 records, the model should order their property damage predictions correctly greater than 75% of the time (that is, it's more important that the property damage values be in the correct order than it is that they be precise with respect to the absolute correct values).

For example, take two random data points, one with a target value of $5000 of damage (A), and one with a target value of $10,000 of damage (B). If the model predicts that B will have a higher damage value than A, that is more valuable than whether it is off by $1000 or $2000 from the correct target value for each.

I'll be validating this as part of the final model evaluation with 100 random samplings of 2 records. It's also more important that records that are farther apart be ordered correctly than ones closer together. Therefore my other expectation is that for every validation trial, the average prediction target difference for accurate ordering is larger than the average prediction target difference for inaccurately OrderedDict pairs.

III. Methodology

Data Preprocessing

The first step I went through was transforming the DBF files into a format I could work with more easily (sqlite), which just involved doing a one-to-one transformation of the tables I cared about (2 out of something like 12 tables) from the DBF files to records in a sqlite database. See the script at "bin/data_to_sqlite" for this transformation.

Step 2 was to take to join together the Fire incidents and Basic incidents tables together into a single tabular row per datapoint for easier fitting to the sklearn models later. The raw data is structured such that a single incident might have data about it denormalized across many tables, but what I cared about for this process was the data in the "Fire incidents" table, and it's accompanying information in the "Basic Incidents" table.

Joining them was a simple matter of iterating through all records in the fire table, finding the accompanying record in the basic table, and joining them together into a single record in the output database for that step. This is done in the script located at "bin/join_incidents_to_one_table"

The NFIRS dataset has a lot of dimensions available. Since I only really have 200k data points to use, I didn't want to include everything because I was concerned about the curse of dimensionality. Due to this, the first major preprocessing step I took was Feature Selection. I took each feature that I though might be relevant and tried to plot it against the target variable (Property Value Loss) to see if it showed a relationship. The "FeatureExploration" notebook contains this work.

As a result of this visualization exercise, I selected the following inputs which seemed to show relevant relationships:

STATE: which US state the incident occurred in *INCIDENT TYPE*: (Cooking fire, chimney fire, portable building fire, outside fire, etc) *AID*: whether help was received from other fire departments *HOUR OF DAY*: What time of day the fire occurred *CONTROLLED TIME*: how long it took the fire department to control the fire *CLEAR TIME*: Time elapsed from arrival to departure of fire protection units *SUPPRESSION_APPARATUS*: How many fire trucks were sent *SUPPRESSION_PERSONNEL*: How many firefighters were dispatched *PROPERTY VALUE*: the initial value of the property on which the fire occurred *DETECTOR ALERT*: was there a fire detector, did it alarm, did it alert the occupants *HAZMAT RELEASE*: what (if any) hazardous or flammable materials were released in the incident (Propane, paint, etc) *PROPERTY_USE*: Primary purpose a building is used for (Mall, Healthcare, Residential, etc) *MIXED_USE*: OTHER purposes a building is used for *NOT_RESIDENTIAL*: if true, building is not used for residential *AREA_ORIGIN*: where did the fire start? (hallway, bedroom, storage) *HEAT_SOURCE*: what started the fire? (Sunlight, static discharge, fireworks, etc) *IGNITION*: Basically was it intentional, an accident, or natural *FIRE_SPREAD*: how far did the fire spread? (object of origin, room of origin, floor of origin, etc) *STRUCTURE_TYPE*: Enclosed Building, Tent, Underground, etc *STRUCTURE_STATUS*: Under construction, normal use, vacant *SQUARE_FEET*: exactly what it sounds like *AES_SYSTEM*: Automatic Extinguishing System

The next step I went through was outlier removal, because there are a lot of values that skew quite heavily to the upper end and they have so much variance, removing outliers entirely seems like the prudent approach for this use case. The incidents that had astronomically high property losses were also obviously catastrophic incidents, and what we're trying to tackle in this problem is revealing relative property loss predictions that might not be immediately obvious to a human actor. I used a normal distribution analysis in a pandas dataframe and found the line where the top

10% of the data set started ($60,000 in damage) and removed all data points with target values above that from the dataset. I also removed data points where we had no incident type or where the incident type was not a fire, since there are many data points for medical or rescue incidents that don't result in property damage at all and those aren't the incidents that we're concerned about for the problem statement mentioned in the use cases at the beginning of this report.

All the work mentioned above so far is done in the "reduce_to_useful_inputs" script in the bin folder. Throughout the project I've tried to make sure each step is a distinct function of the data generated in the step before so that I have checkpoint artifacts of data written to storage along the way after each transformation to play with (this helped enormously in debugging).

In that same script, I also began batching up features that were generating too many dimensions. For example, the "STATE" feature has 50 possible values. Encoding this as a 1-hot vector requires 50 dimensions, and the actual variance it represents is quite tiered, not unique per state. So instead of having 50 categories, I reduced this feature to 3 categories (those abnormally cheap states, those which were abnormally expensive, and the remainder). Many features with a ton of potential options were grouped in similiar ways based on observations in the FeatureExploration notebook (for example, rather than having hours 0-24, we use 3 categories with similar target variable distribution: morning/evening, afternoon, and overnight).

The next step was to clean up the data. There were several records that had many missing values or huge outliers in given inputs. To prevent them from affecting the input too dramatically, I took a few different approaches. For those input features with many values missing, I replaced missing values with the median value for that feature (controlled time, square feet, property value, clear time, suppression apparatus, suppression personnel). For those same features, I'd just remove their data row from the training set entirely if the row had a very large outlier. This process reduced the dataset from about 215k candidate datapoints to about 192k records, and was performed in the script "bin/clean_data".

More preprocessing was still necessary, however, because categorical input dimensions were still represented by integers at this point and continuous data inputs had quite variable scales (apparatus might be anywhere from 2 to 100, but square feet might be 3000 to several hundred thousand) which could have an inadvertent weighting impact on how significantly each input is considered. For categorical inputs, I used 1-hot encoded vectors to make each possible category a binary dimension on it's own. For continuous inputs, I used the min/max of their distribution to transform their values to a floating point number between 0 and 1. This work was done in the script at "bin/normalize_data".

At this point I had a dataset of only relevant records with all the inputs cleaned and processed

ready for training. To make sure I had a validation set left over of totally unseen data to check the real error rate against, I reserved about 30,000 records at this point by removing them from the dataset and writing them to a different datastore (random selection). This work can be seen in the script at "bin/split_off_test_set".

The records ready for training were now available in the sqlite file "data/training_incidents.sqlite".

Implementation

Algorithm Selection

Before commiting to a model for this data, I did an experiment with a series of regression models available in sklearn to see out of the box which ones seemed to score well with minimal tuning. This work is documented in the jupyter notebook entitled "AlgorithmExploration" in the root directory.

My expectation was that the ensemble methods available for regression (particularly those that dependend predominantly on decision trees) would perform far better than naive models because much of the input is categorical rather than continuous, but I didn't want to jump to conclusions like that without the data to support it.

Thanks to the preprocessing covered in the previous section, prep for this exploratory pass was just loading the records from sqlite and shredding them into an array of input vectors and an array of property loss results (with corresponding indexes). I then leveraged the test/train split tools available in sklearn to split both arrays (inputs and results) into a training and test set so that the model would be validated against data it hadn't seen yet.

Then I trained a series of models against the training dataset (inputs and results). First in line was a dummy model, in order to see what a random regression would look like and get a baseline r-squared score for no fit, and a naive linear regression to show the simplest model and how well it could fit a line to the input data. Although several metrics were evaluated to see how the models were performing, I've included only r-squared scores here to keep the summary concise (other fit-scoring function outputs for each model can be seen in the notebook including Mean Squared Error, Mean Absolute Error, and Median Absolute Error).

Model	r-squared score	MSE	RMSE
Dummy	-3.33379834123e-05	4.436	2.106
Linear	0.347285517809	2.895	1.701
Ridge	0.34736410869	2.895	1.701
Lasso	0.154652051569	3.750	1.936
ElasticNet	0.162604152044	3.714	1.927
SGD	0.346010609807	2.901	1.703
Bayseian	0.347298315639	2.895	1.701
PassiveAggressive	-0.217769372351	5.402	2.324
RANSAC	-7.74110759857	38.775	6.227
TheilSen	0.281932204654	3.185	1.784
DecisionTree	0.416033472511	2.590	1.609
ExtraTree	0.26054278424	3.280	1.811
SVM	0.334870023831	2.950	1.718
AdaBoost	0.407018865231	2.630	1.622
Bagging	0.594127375415	1.800	1.341
ExtraTreesEnsemble	0.511182041209	2.168	1.472
GradientBoost	0.63351895371	1.626	1.275
RandomForest	0.618601161064	1.692	1.301

Something to point out here is that the first time I went through this exercise the scores were much lower, with the top r-squared score not being above 0.5. I was surprised at this, but then realized that I had not yet performed the logarithmic transformation on the target variable, and thus the distribution was skewed right. The transformation produced a normal-ish distribution, and rerunning the algorithm exploration notebook produced the data above. Out of this exercise, I selected Bagging, GradientBoost, and RandomForest as algorithms for more parameter tuning to see how they performed

Refinement

At this point I had 3 candidate models which seemed to perform quite well with little tuning. In order to find the hyperparameters for each model with the best score for cross validation within the training set (default scoring function), I made use of the GridSearchCV class within sklearn. This involved selecting potential parameter grids for each model and running the grid search over them to select the parameter combination that scored the best error rate for the provided training data.

The work described here was done in the "bin/tune_params" script. By running through combinations of parameters exhaustively I was able to obtain a best score for each of the 3 models, and then compare them for final model selection.

For the RandomForestRegressor, the input parameter grid looked like this:

```
{
  'min_samples_split': [5,9],
  'min_samples_leaf': [1,3,5],
  'n_estimators': [10,100,250],
  'max_depth': [2,3,5]
}
```

Remember, this means train a model for every combination of params here (*2*3*3 models) and comparing the scores; this took about an hour per model. The top scoring Random Forest model produced a score of 0.575212520004.

For the BaggingRegressor, the input parameter grid looked like this:

```
{
  'max_features': [1.0,0.75,0.5],
  'n_estimators': [10,25,50],
  'max_samples': [1.0,0.75,0.5]
}
```

And the top scoring Bagging model got 0.632741581369

For the GradientBoostingRegressor the input parameter grid looked like this:

```
{
  'min_samples_split': [5,9],
  'min_samples_leaf': [1,3,5],
  'n_estimators': [100,250],
  'max_depth': [2,3,5]
}
```

And the top scoring GradientBoostingRegressor got 0.636959489576.

This means that Gradient boost was technically the highest scoring model after tuning (even though Bagging is so close as to be nearly indistinguishable), and it's final input parameters for the best score turned out to be as follows:

alpha=0.9 init=None learning_rate=1.0 loss='ls' max_depth=3 max_features=None max_leaf_nodes=None min_samples_leaf=5 min_samples_split=5 min_weight_fraction_leaf=0.0 n_estimators=100 presort='auto' random_state=None subsample=1.0 verbose=0

warm_start=False

At this point I took the Gradient Boosting Regressor on to validation with the 30,000 reserved data points to make sure it wasn't overfit to the data in the test/train split.

IV. Results

Model Evaluation and Validation

After the data preprocessing there were about 30,000 records reserved to use once training was fully complete to validate the model against data it had never seen before (even in test sets). The plan was to compare r^2 scores and MSE (Mean Squared Error)/RMSE between the results obtained in the model selection and tuning passes and confirm that they weren't a result of overfitting.

In model selection the Gradient Boost model with no tuning turned up a Mean Squared Error of 1.634. This is difficult to put in context because it's the squared difference between two logarithmically transformed values. For comparison, the dummy (random) regression model produced an MSE of 4.436 (RMSE 2.106), and the naive linear regression scored an MSE of 2.895 (RMSE 1.701). Looking at R^2 values, they're similarly ordered. Dummy: -3.334, Linear: 0.347, GradientBoost: 0.634. In both metrics you can see that gradient boost gives meaningful (non-random) information, and performs better than a naive model.

After tuning the model, Gradient Boost with ideal parameters produced an r^2 value of 0.637 (not very much better, really, so tuning didn't gain too much according to r^2).

The first question is whether that has been overfit to the training/test data or not. In the model evaluation work done in the "ModelValidation" notebook, I found a Mean Squared Error of 1.431 (RMSE 1.196) and an R^2 score of 0.677. This would appear to indicate both that tuning *was* meaningful (MSE has come down) and that the model generalizes well to unseen data (MSE and R^2 both are pretty close to original values, better in fact).

Next we want to ask whether the model is robust to small changes in inputs. Most of the input data is categorical, so it's hard to decide what "small" changes are for those. I did some input manipulation in the script "./bin/example_prediction_leverage" to make sure that changing categories didn't produce extreme differences. Here's the output from that portion of the script:

```
MADE UP FULL INPUT
{'AES_PRES': '2', 'AREA_ORIG': '4', 'ALARM': '112520110256', 'MIXED_USE': '5
8', 'AID': 2, 'HEAT_SOURC': '7', 'FIRE_SPRD': '4', 'HAZ_REL': 6, 'STRUC_STAT
': '6', 'INC_TYPE': 13, 'SUP_APP': 8, 'NOT_RES': '1', 'PROP_USE': '7', 'DET_
ALERT': '2', 'CAUSE_IGN': '4', 'STATE': 'CA', 'STRUC_TYPE': '4', 'SUP_PER':
24, 'INC_CONT': '112520110310', 'TOT_SQ_FT': 5000, 'LU_CLEAR': '112520110500
', 'PROP_VALUE': 180000}
PREDICTION
$ 4628.92
SENSITIVITY ANALYSIS , normal changes
Alarm to middle of morning
$ 5059.3
increase responding units
$ 6587.37
decrease property value by 20 grand
$ 6878.79
change hazmat release type
$ 13961.78
knock 20 percent off of square footage
$ 11846.7
```

None of these changes from prediction to prediction seem unreasonable, though that's a very subjective judgement. For the continuous fields, I did perform small changes and found they impacted the output not at all:

```
knock 20 percent off of square footage
$ 11846.7
SENSITIVITY ANALYSIS , tiny changes
add 100 square feet
$ 11846.7
change property value by $1000
$ 11846.7
```

This is because decision trees factor heavily into the model, and they are going to find threshold values to change their output weights at. This seems to indicate the model is robust to tiny changes in input.

Justification

There are two subjects to address here. First, did the final model perform well relative to the dummy (random) regression? Yes, most definitey, and this is discussed in the Model Evaluation

and Validation section above.

The more important subject here is whether this model meets expectations for being used in some of the use cases described at the beginning of this report. The benchmark established in the "Benchmark" section above was that for any random set of 2 records, the model should order their property damage predictions correctly greater than 75% of the time, and that the average prediction target difference for accurate ordering is larger than the average prediction target difference for inaccurately OrderedDict pairs. This expectation is validated in the "ModelValidation" notebook where I took 10 passes through the validation process, each time selecting 100 pairs of data points and seeing if the model correctly ordered their predictions (predicted the correct point of the 2 to have the higher property damage value). I also stored the difference between the predicted value and the actual damage value (in dollars, not logarithmic value) so that I could get the average data point difference for the correctly ordered pairs and the incorrectly ordered pairs. That data is included here:

```
TRIAL 1
CORRECT 84, AVG DELTA 11276.3690476
INCORRECT 16, AVG DELTA 6631.25
------------
TRIAL 2
CORRECT 76, AVG DELTA 13588.9605263
INCORRECT 24, AVG DELTA 4934.04166667
------------
TRIAL 3
CORRECT 83, AVG DELTA 16471.9156627
INCORRECT 17, AVG DELTA 7952.88235294
------------
TRIAL 4
CORRECT 85, AVG DELTA 14023.7647059
INCORRECT 15, AVG DELTA 5026.66666667
------------
TRIAL 5
CORRECT 81, AVG DELTA 14575.6790123
INCORRECT 19, AVG DELTA 7829.68421053
------------
TRIAL 6
CORRECT 81, AVG DELTA 15550.7777778
INCORRECT 19, AVG DELTA 5907.89473684
------------
TRIAL 7
CORRECT 81, AVG DELTA 14842.0864198
INCORRECT 19, AVG DELTA 7233.21052632
------------
TRIAL 8
CORRECT 84, AVG DELTA 12543.3690476
INCORRECT 16, AVG DELTA 7277.8125
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TRIAL 9
CORRECT 84, AVG DELTA 10724.702381
INCORRECT 16, AVG DELTA 7703.0625
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TRIAL 10
CORRECT 85, AVG DELTA 13098.0117647
INCORRECT 15, AVG DELTA 7410.0
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We can see in the above data set that both expectations are met. In each trial, greater than 75% of the pairs are ordered correctly; and in each trial the average delta for the correctly ordered pairs was significantly greater than the average delta for the incorrectly ordered pairs. This indicates to me that based on the constraints stated in the problem description, this model is sufficient to act in those capacities.

V. Conclusion

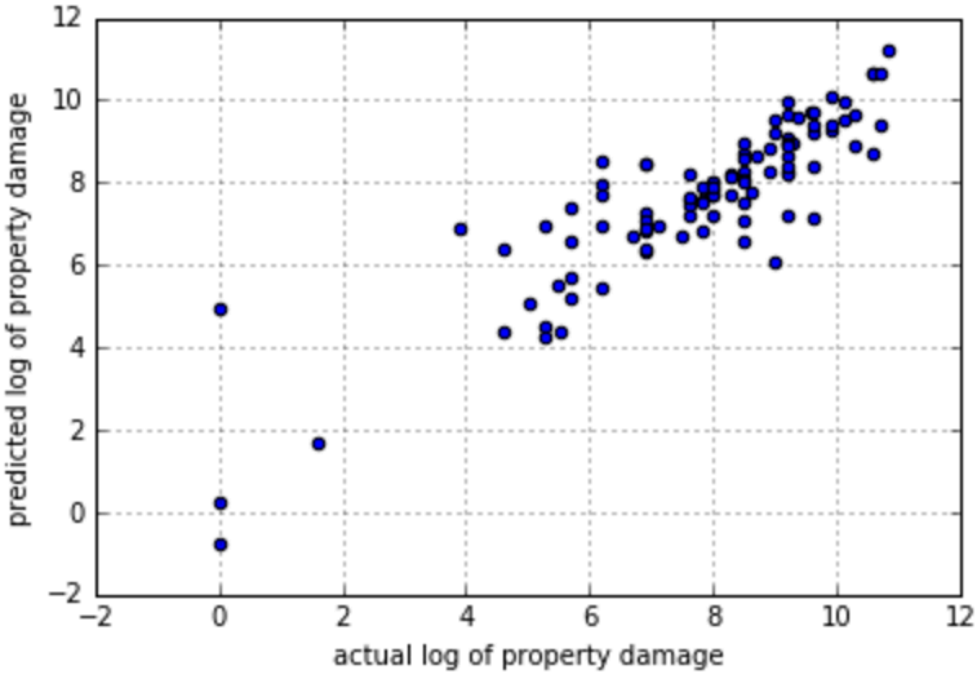
Free-Form Visualization

Although the R-squared scores and benchmarks look good for the model, it's also useful to get an intuitive feeling for how well the model predicts the actual values for unseen data. For that reason in the notebook named ResultVisualization I took some time to look at the distribution of predictions with respect to the actual values to see how well the correlated visually.

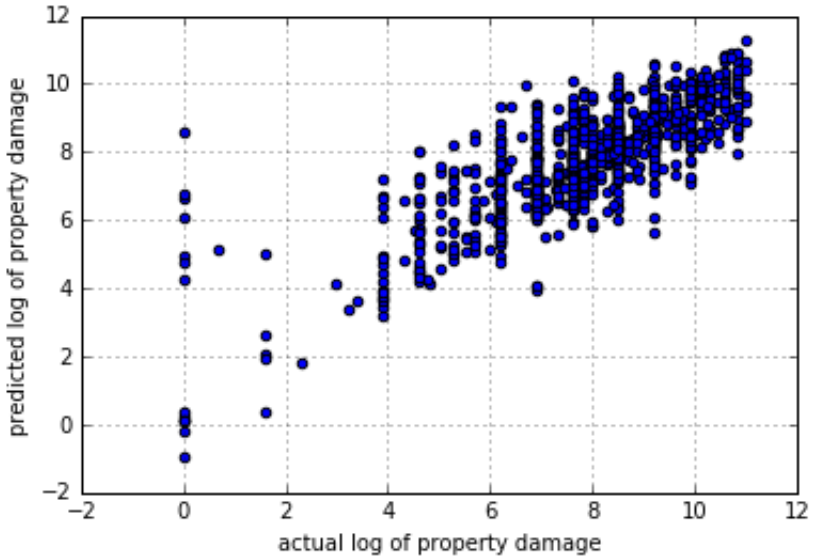
To do this I built a function that takes in the actual labels for the 30,000 record validation set and the predicted labels from the persisted model, and seven times generated a list of 100 indexes at random to plot together to see how they lined up. This produced 7 graphs (all visible in that notebook) which show how well the predictions and actual values match.

If the match were perfect, then the scatterplot would be just a straight line of points traveling along the line defined by y = x. If the predictions were poor, the plots would look aimless, or at least not very much like a line of best fit would travel along y = x.

All the generated plots looked very similar to this one:



And the very last plot I generated had 1000 data points instead of 100.
It's harder to get a feel for individual outliers, but it's clear how dense the predictions are with respect to the actual values in the thickest part of the cloud:



In both charts you should be able to see the suggestion of a linear relationship between the two,

and that it sticks reasonably close to y = x.

Reflection

There are many observations that come to mind when thinking back over the course of this project. The loudest one in my mind is that data cleaning and feature selection is by far where most of my time was spent. To break the project into stages, I would structure it thusly (in order with percentage of time spent there):

- Project Ideation (4%)
- Dataset selection (3%)
- Feature exploration (18%)
- Feature selection (12%)
- Data cleaning (15%)
- Data Normalization (15%)
- Model exploration (8%)
- Model selection (2%)
- Model tuning (6%)
- Model verification and debugging (10%)
- Project Writeup (7%)

Although the learning algorithms themselves are the most intellectually interesting part of the whole process, learning the data and massaging it into a useful format is really where most of my efforts were allocated.

Another notable item was the points at which I ran into problems and had to go back and fix a transformation in pre-processing or something similar. For example, it wasn't until I was validating the model that I though very much about the distribution of the target variable. Seeing it cluster so far towards the origin made me concerned that regression algorithms would be making bad assumptions about the distribution.

I went back to the AlgorithmExploration notebook and transformed the data in place to log-of-target and found a 0.1 jump on average in R-squared scores, and so I had to go back to the "normalize" step in my data transformation pipeline and re-run the steps from there forward to take that preferred coordination into account. This made me *very* glad that I had kept artifacts from each transformation along the way; rather than having to run the whole preprocessing pipeline from scratch, I was able to pick up at the first point in the pipeline that cared about the particular

data shape I was trying to impact and just re-run steps from there forward. I'll plan on continuing to use this pattern in future projects.

Based on the rather lenient benchmarks I defined to represent success for the use cases I was considering approaching this problem for, I'm pretty satisfied that the model as it is would solve it well enough for general application. I still have some ideas for how to improve the model (see improvement section below) and if I were packaging this model into a software solution that was taking on real production subscribers, then I'd want to pursue some of those avenues first.

Improvement

The first and most obvious way to improve this model is to start taking in more data. I only made use of the NFIRS data from 2011 because it was easy to get ahold of as a unit for general research, but NFIRS has data for every year since the 70s and up until this year, and it's possible I could make use of all of it to further tune the precision of the model. Some cleaning would have to be done to account for inflation, since property values can change significantly over a few decades (probably pick yearly inflation numbers and normalize all data to 2016 dollars). I would also want to find some way to weight more recent data points because fire behavior is different in structures built recently with open floor plans and lightweight construction materials.

It's also possible that regression isn't the right way to model this problem for general application. In thinking about what I would really want to get out of this system as a first due officer or a dispatcher, I'd probably be mapping these projected numbers to tiered thresholds that I'd call "no big deal", "kinda problematic", "absolutely catastrophic", etc. We could actually do one better for them and save a mental step by categorizing these damage levels (perhaps by absolute dollar value or by dollar value as a ratio to property value), and having the label output from the model be a category rather than a specific dollar figure. This turns the whole thing into a classification problem, and at that point I might consider leveraging tensorflow and building a deep neural network (I'm given to understand that neural networks may be overkill for regression problems). I would care more about precision in this case (getting the category right would be very important), but it's also a softer target to hit. This improvement would require soliciting feedback from those with more domain expertise than I, though.