In [3]:
```
# Pandas and numpy for data manipulation
import pandas as pd
import numpy as np

# No warnings about setting value on copy of slice
pd.options.mode.chained_assignment = None
pd.set_option('display.max_columns', 60)

# Matplotlib for visualization
import matplotlib.pyplot as plt
%matplotlib inline

# Set default font size
plt.rcParams['font.size'] = 24

from IPython.core.pylabtools import figsize

# Seaborn for visualization
import seaborn as sns

sns.set(font_scale = 2)

# Imputing missing values
from sklearn.preprocessing import Imputer, MinMaxScaler

# Machine Learning Models
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import GradientBoostingRegressor

from sklearn import tree

# LIME for explaining predictions
import lime
import lime.lime_tabular
```

In [5]:
```
# Read in data into dataframes
train_features = pd.read_csv('training_features.csv')
test_features = pd.read_csv('testing_features.csv')
train_labels = pd.read_csv('training_labels.csv')
test_labels = pd.read_csv('testing_labels.csv')
```

In [6]:
```
# Create an imputer object with a median filling strategy
imputer = Imputer(strategy='median')

# Train on the training features
imputer.fit(train_features)

# Transform both training data and testing data
X = imputer.transform(train_features)
X_test = imputer.transform(test_features)

# Sklearn wants the labels as one-dimensional vectors
y = np.array(train_labels).reshape((-1,))
y_test = np.array(test_labels).reshape((-1,))
```

In [7]:
```
# Function to calculate mean absolute error
def mae(y_true, y_pred):
    return np.mean(abs(y_true - y_pred))
```

In [8]:
```

model = GradientBoostingRegressor(loss='lad', max_depth=5, max_features=None,
                                  min_samples_leaf=6, min_samples_split=6,
                                  n_estimators=800, random_state=42)


model.fit(X, y)
```

Out[8]:
```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.1, loss='lad', max_depth=5, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=6,
             min_samples_split=6, min_weight_fraction_leaf=0.0,
             n_estimators=800, presort='auto', random_state=42,
             subsample=1.0, verbose=0, warm_start=False)
```

In [9]:
```

#  Make predictions on the test set
model_pred = model.predict(X_test)

print('Final Model Performance on the test set: MAE = %0.4f' % mae(y_test, model_
```

```
Final Model Performance on the test set: MAE = 9.0837
```

In [10]:
```
# Extract the feature importances into a dataframe
feature_results = pd.DataFrame({'feature': list(train_features.columns),
                                'importance': model.feature_importances_})

# Show the top 10 most important
feature_results = feature_results.sort_values('importance', ascending = False).r

feature_results.head(10)
```

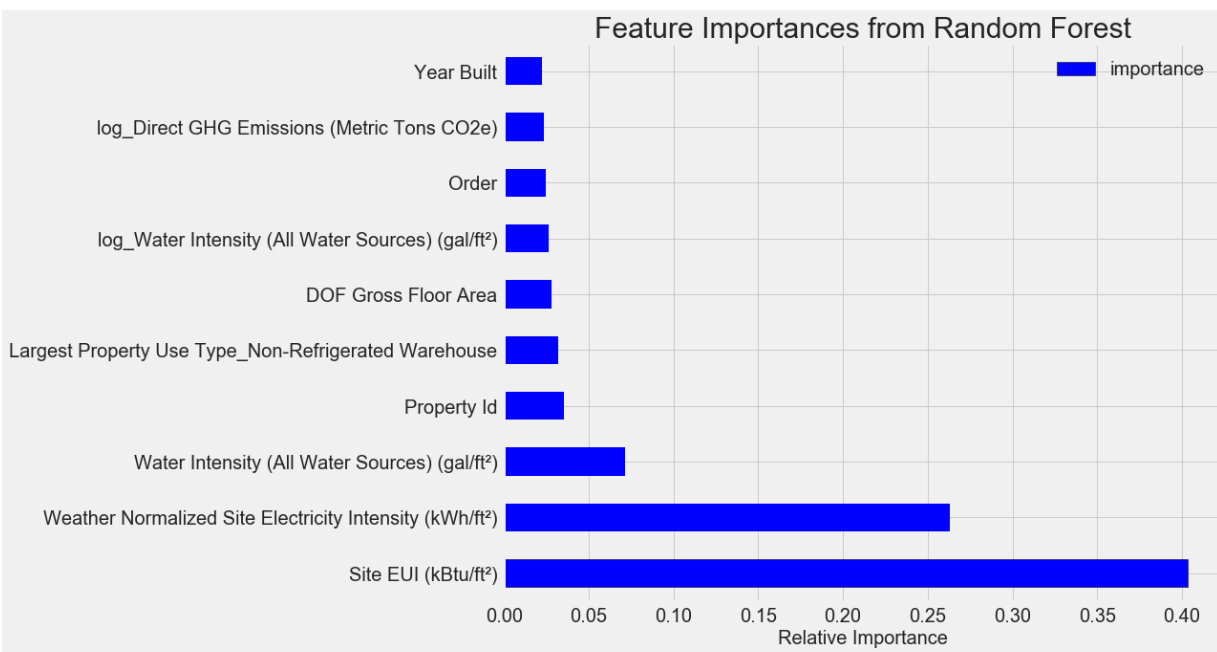
Out[10]:

	feature	importance
0	Site EUI (kBtu/ft²)	0.403532
1	Weather Normalized Site Electricity Intensity ...	0.263059
2	Water Intensity (All Water Sources) (gal/ft²)	0.071286
3	Property Id	0.035165
4	Largest Property Use Type_Non-Refrigerated War...	0.031924
5	DOF Gross Floor Area	0.027900
6	log_Water Intensity (All Water Sources) (gal/ft²)	0.026058
7	Order	0.024592
8	log_Direct GHG Emissions (Metric Tons CO2e)	0.023655
9	Year Built	0.022100

In [11]:

```
figsize(12, 10)
plt.style.use('fivethirtyeight')

# Plot the 10 most important features in a horizontal bar chart
feature_results.loc[:9, :].plot(x = 'feature', y = 'importance',
                                 edgecolor = 'k',
                                 kind='barh', color = 'blue');
plt.xlabel('Relative Importance', size = 20); plt.ylabel('')
plt.title('Feature Importances from Random Forest', size = 30);
```

```
c:\users\mglewis\appdata\local\programs\python\python36\lib\site-packages\matpl
otlib\font_manager.py:1331: MatplotlibDeprecationWarning: matplotlib.verbose is
deprecated;
Command line argument --verbose-LEVEL is deprecated.
This functionality is now provided by the standard
python logging library.  To get more (or less) logging output:
    import logging
    logger = logging.getLogger('matplotlib')
    logger.set_level(logging.INFO)
  (prop, best_font.name, repr(best_font.fname), best_score))
c:\users\mglewis\appdata\local\programs\python\python36\lib\site-packages\matpl
otlib\__init__.py:356: MatplotlibDeprecationWarning: matplotlib.verbose is depr
ecated;
Command line argument --verbose-LEVEL is deprecated.
This functionality is now provided by the standard
python logging library.  To get more (or less) logging output:
    import logging
    logger = logging.getLogger('matplotlib')
    logger.set_level(logging.INFO)
  @cbook.deprecated("2.1")
```



In [12]:
```
# Extract the names of the most important features
most_important_features = feature_results['feature'][:10]

# Find the index that corresponds to each feature name
indices = [list(train_features.columns).index(x) for x in most_important_feature

# Keep only the most important features
X_reduced = X[:, indices]
X_test_reduced = X_test[:, indices]

print('Most important training features shape: ', X_reduced.shape)
print('Most important testing  features shape: ', X_test_reduced.shape)
```

```
Most important training features shape:  (6622, 10)
Most important testing  features shape:  (2839, 10)
```

In [13]:
```
lr = LinearRegression()

# Fit on full set of features
lr.fit(X, y)
lr_full_pred = lr.predict(X_test)

# Fit on reduced set of features
lr.fit(X_reduced, y)
lr_reduced_pred = lr.predict(X_test_reduced)

# Display results
print('Linear Regression Full Results: MAE =    %0.4f.' % mae(y_test, lr_full_pr
print('Linear Regression Reduced Results: MAE = %0.4f.' % mae(y_test, lr_reduced_
```

```
Linear Regression Full Results: MAE =    13.4651.
Linear Regression Reduced Results: MAE = 15.1007.
```

In [14]:
```

# Create the model with the same hyperparamters
model_reduced = GradientBoostingRegressor(loss='lad', max_depth=5, max_features=
                                  min_samples_leaf=6, min_samples_split=6,
                                  n_estimators=800, random_state=42)

# Fit and test on the reduced set of features
model_reduced.fit(X_reduced, y)
model_reduced_pred = model_reduced.predict(X_test_reduced)

print('Gradient Boosted Reduced Results: MAE = %0.4f' % mae(y_test, model_reduce
```

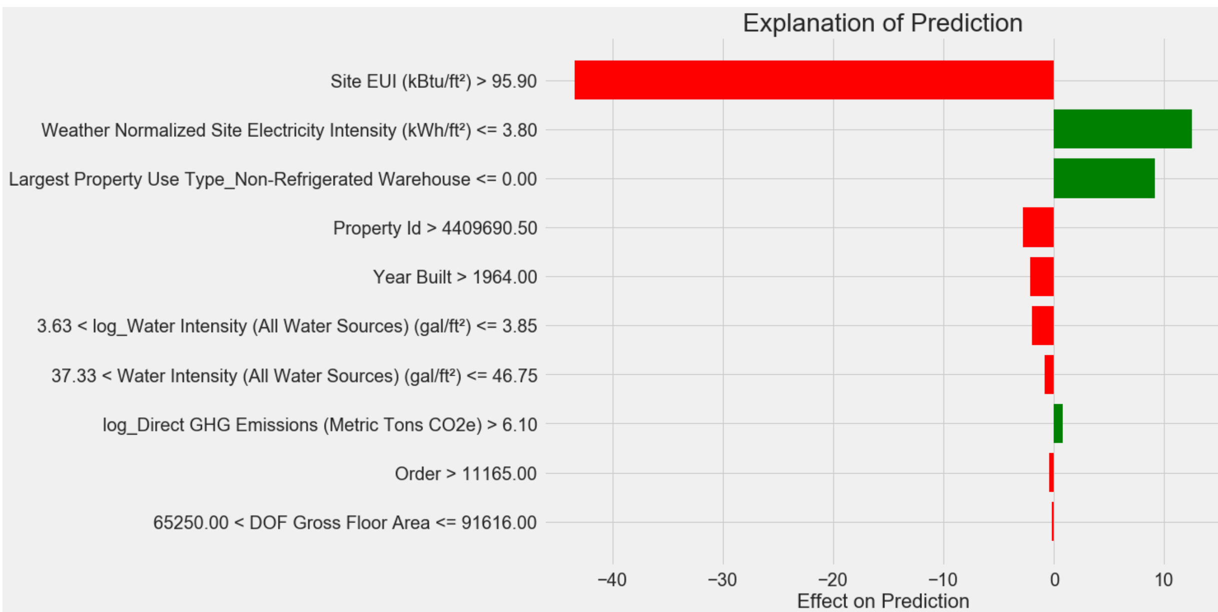
```
Gradient Boosted Reduced Results: MAE = 10.8594
```

In [15]:
```

# Find the residuals
residuals = abs(model_reduced_pred - y_test)

# Exact the worst and best prediction
wrong = X_test_reduced[np.argmax(residuals), :]
right = X_test_reduced[np.argmin(residuals), :]
```

In [16]:
```
# Create a lime explainer object
explainer = lime.lime_tabular.LimeTabularExplainer(training_data = X_reduced,
                                                   mode = 'regression',
                                                   training_labels = y,
                                                   feature_names = list(most_impo
```

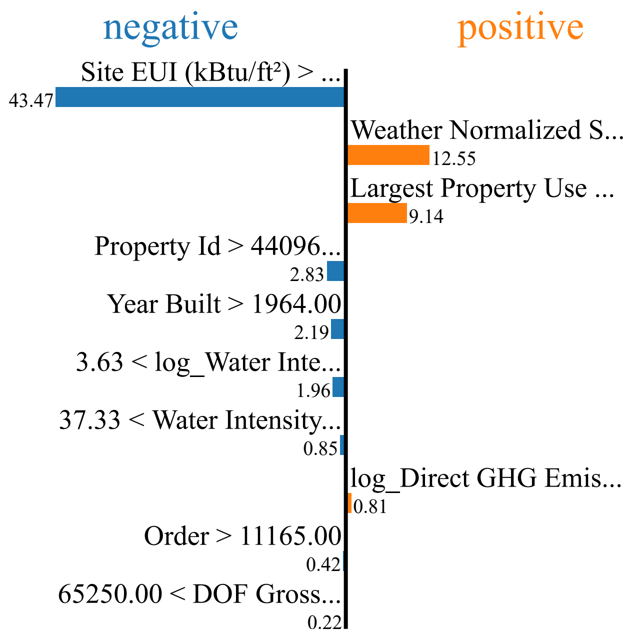
In [17]:
```

# Display the predicted and true value for the wrong instance
print('Prediction: %0.4f' % model_reduced.predict(wrong.reshape(1, -1)))
print('Actual Value: %0.4f' % y_test[np.argmax(residuals)])

# Explanation for wrong prediction
wrong_exp = explainer.explain_instance(data_row = wrong,
                                       predict_fn = model_reduced.predict)

# Plot the prediction explaination
wrong_exp.as_pyplot_figure();
plt.title('Explanation of Prediction', size = 28);
plt.xlabel('Effect on Prediction', size = 22);
```

```
Prediction: 12.8615
Actual Value: 100.0000
```



In [18]:

```
wrong_exp.show_in_notebook(show_predicted_value=False)
```

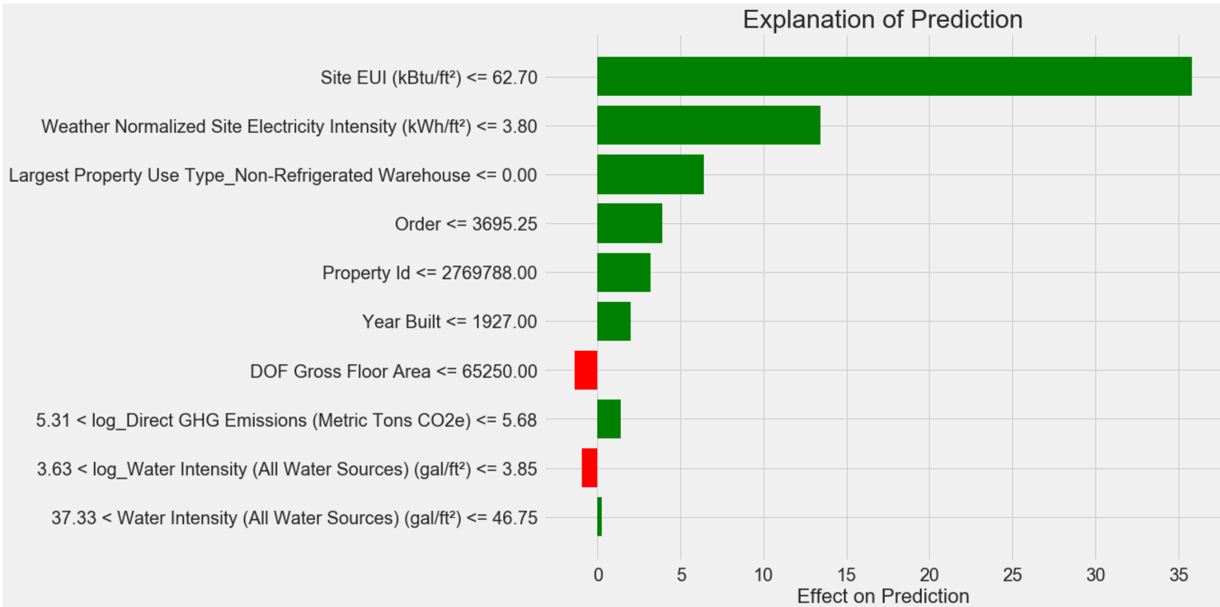


Site EUI (kBtu/ft²)	144.90
Weather Normalized Site Electricity Intensity (kWh/ft²)	3.20
Largest Property Use Type_Non-Refrigerated Warehouse	0.00
Property Id	4495603.00
Year Built	1969.00
log_Water Intensity (All Water Sources) (gal/ft²)	3.85
Water Intensity (All Water Sources) (gal/ft²)	46.75
log_Direct GHG Emissions (Metric Tons CO2e)	6.18
Order	14736.00
DOF Gross Floor Area	67914.00

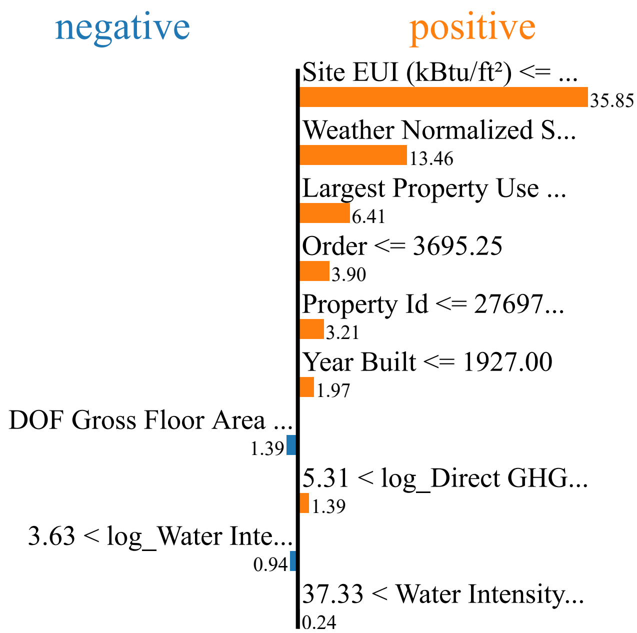
In [19]:

```
# Display the predicted and true value for the wrong instance
print('Prediction: %0.4f' % model_reduced.predict(right.reshape(1, -1)))
print('Actual Value: %0.4f' % y_test[np.argmin(residuals)])

# Explanation for wrong prediction
right_exp = explainer.explain_instance(right, model_reduced.predict, num_feature
right_exp.as_pyplot_figure();
plt.title('Explanation of Prediction', size = 28);
plt.xlabel('Effect on Prediction', size = 22);
```

```
Prediction: 100.0000
Actual Value: 100.0000
```



In [20]:
```
right_exp.show_in_notebook(show_predicted_value=False)
```



Site EUI (kBtu/ft²)	0.10
Weather Normalized Site Electricity Intensity (kWh/ft²)	0.00
Largest Property Use Type_Non-Refrigerated Warehouse	0.00
Order	92.00
Property Id	2658213.00
Year Built	1924.00
DOF Gross Floor Area	50120.00
log_Direct GHG Emissions (Metric Tons CO2e)	5.68
log_Water Intensity (All Water Sources) (gal/ft²)	3.85
Water Intensity (All Water Sources) (gal/ft²)	46.75

In [22]:
```
# Extract a single tree
single_tree = model_reduced.estimators_[105][0]

tree.export_graphviz(single_tree, out_file = 'tree.dot',
                     rounded = True,
                     feature_names = most_important_features,
                     filled = True)

single_tree
```

Out[22]:
```
DecisionTreeRegressor(criterion='friedman_mse', max_depth=5,
           max_features=None, max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=6, min_samples_split=6,
           min_weight_fraction_leaf=0.0, presort='auto',
           random_state=<mtrand.RandomState object at 0x000001C535CE9E10>,
           splitter='best')
```

In [23]:
```
# Convert to a png from the command line
# This requires the graphviz visualization library (https://www.graphviz.org/)


# !dot -Tpng images/tree.dot -o images/tree.png
```

In [25]:
```

tree.export_graphviz(single_tree, out_file = 'tree_small.dot',
                     rounded = True, feature_names = most_important_features,
                     filled = True, max_depth = 3)
```

In [ ]:
```
```