In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

In [52]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib

import random
import re
from collections import defaultdict
import glob
from pyitlib import discrete_random_variable as drv
import _pickle as cPickle
import zlib

import matplotlib.pyplot as plt
from scipy.stats import skew
from scipy.stats.stats import pearsonr
import xgboost as xgb
from lightgbm import LGBMRegressor

from sklearn.ensemble import RandomForestRegressor, StackingRegressor
from sklearn.model_selection import KFold, cross_val_score, GridSearchCV, cros
s_validate
from sklearn.metrics import make_scorer, mean_squared_error
from sklearn.linear_model import Ridge, RidgeCV, ElasticNet, LassoCV, LassoLar
sCV, Lasso
from sklearn.svm import SVR

%config InlineBackend.figure_format = 'retina' #set 'png' here when working on
notebook
%matplotlib inline
```

In [3]:
```
RANDOM_STATE = 50
```

Assignment completed by:
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Mason Valicek
Alejandro Rodriguez

Problem 1

Read Shannon’s 1948 paper ’A Mathematical Theory of Communication’. Focus on pages 1-19 (upto Part II), the remaining part is more relevant for communication.

The central goal of this paper is to find a general theory of communication. The fundamental problem of communication lies in the reproduction of messages between a source and destination for a communication system. Sometimes the correct message to be reproduced must be selected from a group of possible messages. If each message in the group has an equally likely choice of being the correct original message, you can use a logarithmic function to estimate the amount of information being sent.

A communication system has five parts: an information source that produces a message, a transmitter that transforms the message somehow to make it transferable, a channel that transports the message from a transmitter to the receiver, a receiver that performs the inverse transformation of the transmitter, and finally a destination that gets the message from the receiver. There are three types of information systems: discrete, continuous, and mixed. Noise is also introduced to the channel. A key aspect to a communications system is how that noise can be filtered out to properly extract the original message.

One central question is how can we measure the capacity of a channel to transmit information. There is a formula for it, C = Lim(T->infinity) [logN(T) / T], and you can also always condense discrete sequences by only tracking changes in state. A communication system that uses discrete symbols with probabilities of being chosen is known as a stochastic process. We can approximate the english language by increasing the order of approximation in the stochastic process. A stochastic process is also known as a discrete Markhoff process. We can represent these Markhoff processes as state diagrams with probabilities connected to state changes. There’s a group of markhoff processes called ergodic processes, which are basically graphs where every node is connected to every other node, with a path back (not periodic). If graphs are disjoint, they can be split into multiple ergodic processes.

H(p1,...,pn) defines the ‘uncertainty’ of an event, and this uncertainty should increase linearly with ‘n’ if pi = 1/n for all i < n. We know that H = -Ksum(pi(log(pi)) where K is a positive constant. We can also find the entropy of each finite state from a discrete finite state source. The mathematical operations used to code and decode information comprise a discrete transducer. Additionally the output of the a finite state transducer is a finite state statistical source with an entropy H less than or equal to the entropy of the input. If a source has entropy H and a channel capacity C, we can encode the source output at an average rate greater than C/H.

Problem 2

ICML is a top research conference in Machine learning. Scrape all the pdfs of all ICML 2017 papersfrom [http://proceedings.mlr.press/v70/ (http://proceedings.mlr.press/v70/)](http://proceedings.mlr.press/v70/)

In [10]:
```python
# Gets a dataframe of all alphanumeric words, repeats possible
word_dict = {'word' : [], 'source' : []}

txt_doc_names = glob.glob("*.txt")
txt_doc_names.sort()

for txt_doc_name in txt_doc_names:
    with open(txt_doc_name, 'r', encoding="utf-8") as file:
        words = file.read().replace('\n', ' ').replace('_', '')
    pattern = re.compile('[^\w\s]')
    words = pattern.sub(' ', words)
    pattern = re.compile('CID:\S+')
    words = pattern.sub('', words)
    word_list = words.split()

    for word in word_list:
        word = word.lower()
        if (word != ' ') and (len(word) > 0) and (word[0] != ' ') and (word != 
len(word) * word[0]):
            pattern = re.compile('[\s]')
            word = pattern.sub('', word)
            word_dict['word'].append(word)
            word_dict['source'].append(txt_doc_name)

word_df = pd.DataFrame(word_dict, columns = ['word', 'source'])
```

In [11]:
```
# Creates a dataframe where each word and punctuation symbol is a row, with re
peated words possible
word_punc_dict = {'word' : [], 'source' : []}

txt_doc_names = glob.glob("*.txt")
txt_doc_names.sort()

for txt_doc_name in txt_doc_names:
    with open(txt_doc_name, 'r', encoding="utf-8") as file:
        words = file.read().replace('-\n', '').replace('\n', ' ')

    pattern = re.compile('\(CID\S+')
    words = pattern.sub(' ', words)
    pattern = re.compile('\(cid\S+')
    words = pattern.sub(' ', words)
    pattern = re.compile('\<\S+')
    words = pattern.sub(' ', words)

    word_list = re.split('(\W+)', words)

    for word in word_list:
        word = word.lower()
        if (len(word) > 0) and (word[0] != ' ') and (word != len(word) * word[
0]):
            pattern = re.compile('[\s]')
            word = pattern.sub('', word)
            if (len(word) > 1) and not word.isalnum():
                chars = list(word)
                for char in chars:
                    word_punc_dict['word'].append(char)
                    word_punc_dict['source'].append(txt_doc_name)
            else:
                word_punc_dict['word'].append(word)
                word_punc_dict['source'].append(txt_doc_name)

word_punc_df = pd.DataFrame(word_punc_dict, columns = ['word', 'source'])
```

1. What are the top 10 common words in the ICML papers?

In [12]:
```
print(word_df['word'].value_counts().head(10))
```

```
the     146786
of       74319
and      64278
in       51415
to       49339
is       39234
for      35933
we       33331
that     24167
with     21310
Name: word, dtype: int64
```

2. Let Z be a randomly selected word in a randomly selected ICML paper. Estimate the entropy of Z.

To calculate entropy meant calculating all joint and conditional probabilities for words and sources in all texts. This is possible, but not on my machine, since there are so many words in the original dataframe. There are two ways I found to do this: first by getting the value from base probabilities, second by using an external library. The last command is runnable, and has the fastest runtime, but I do not have enough memory to run it.

In [ ]:

```
# Method 1 calculating probability by probability (logic is there, I just coul
dn't run it)

def prob_dict(a):
    # Make dictionary of probabilities
    a_list = a.tolist()

    a_counts = {}
    total = len(a_list)

    for key in a_list:
        if key in a_counts:
            a_counts[key] = a_counts[key] + 1
        else:
            a_counts[key] = 1

    a_probs = a_counts

    for key in a_probs.keys():
        a_probs[key] = a_probs[key]/total

    return(a_probs)

def count_arr(df):
    df_arr = np.array(df)

    a = df['word']
    b = df['source']
    b_unq = b.unique()
    a_unq = a.unique()

    b_map = {}
    ind = 0
    for item in b_unq:
        b_map[item] = ind
        ind += 1

    a_map = {}
    ind = 0
    for item in a_unq:
        a_map[item] = ind
        ind += 1

    count_arr = np.zeros((len(a_map.keys()), len(b_map.keys())))
    count_len = len(df_arr)
    for i in range(count_len):
        a_val = df_arr[i][0]
        b_val = df_arr[i][1]
        a_ind = a_map[a_val]
        b_ind = b_map[b_val]
        count_arr[a_ind][b_ind] += 1

    return(count_arr)

def joint_prob_arr(df):
    counts = count_arr(df)
    joint_probs = counts

    for i in range(len(counts)):
        for j in range(len(counts[0])):
            joint_probs[i][j] = (1/len(counts[0]))*(counts[i][j]/np.sum(counts
[:,j]))

    return(joint_probs)

def cond_prob_arr(df, joint_probs):
    a = df['word']
    a_probs = prob_dict(a)
    a_unq = a.unique()
    a_map = {}
    ind = 0
    for item in a_unq:
        a_map[ind] = item
        ind += 1

    cond_probs = joint_probs

    for i in range(len(joint_probs)):
        for j in range(len(joint_probs[0])):
            cond_probs[i][j] = joint_probs[i][j]/a_probs[a_map[i]]

    return(cond_probs)

def cond_entropy(df):
    joint_probs = joint_prob_arr(df)
    cond_probs = cond_prob_arr(df, joint_probs)

    sum = 0
    for i in range(len(joint_probs)):
        for j in range(len(joint_probs)[0]):
            sum += joint_probs[i][j]*np.log2(cond_probs[i][j])

    return(sum)
    # Make 2-D array of conditional probabilities

    # Calculate conditional entropy
```

In [ ]:
```python
# Alternative of method 1, more condensed but less efficient
def get_joint_prob(word, source, df):
    word_freq = df[df['source'] == source][df['word'] == word].shape[0]
    words_in_source = df[df['source'] == source].shape[0]
    num_sources = df['source'].unique().shape[0]
    prob = (1 / num_sources) * (word_freq / words_in_source)
    return(prob)

def get_prob(word, df):
    word_freq = df[df['word'] == word].shape[0]
    total_words = df.shape[0]
    prob = word_freq / total_words
    return(prob)

def get_cond_prob(word, source, df):
    prob = get_prob(word, df)
    joint = get_joint_prob(word, source, df)
    cond = joint / prob
    return(cond)

def get_cond_entropy(df):
    unique_sources = df['source'].unique().tolist()
    sum = 0
    for source in unique_sources:
        unique_words = df[df['source'] == source]['word'].unique().tolist()
        for word in unique_words:
            sum += get_joint_prob(word, source, df) * np.log2(get_cond_prob(wo
rd, source, df))
    return(-sum)
```

In [ ]:
```python
# Method 2, external library
drv.entropy_conditional(word_df['word'].tolist(), word_df['source'].tolist())
```

3. Synthesize a random paragraph using the marginal distribution over words.

In [13]:
```
NUM_PARA_WORDS = 100
para = ''
num_words = word_df.shape[0]

for i in range(NUM_PARA_WORDS):
    word_ind = np.random.randint(num_words)
    word = word_df.iat[word_ind, 0] + ' '
    para = para + word

print(para)
```

```
low users union for normal isbn to processes commits optimal we but satisfy a
t animal 009 real can sum most that model sources finding initialized project
s would do the comparatively leibe mcmc fixed joint finite 2011 proof resulti
ng which symposium programming as conditional that corresponding vk framework
the filter further of sharp gaps is on in to gain exploration neural solved o
f fqi details allocation 96 aaai tricks and of sec and the addition proofs co
loring is 2016a software 50000 them in hand is practical otherwise trans 2016
updater in assigned expression zi with kd number barycenter unified eugene ba
sed
```

4. (Extra credit) Synthesize a random paragraph using an n-gram model on words. Synthesize a random paragraph using any model you want. Top five synthesized text paragraphs win bonus (+30 points)

To make our n-gram model have a bit more variance than a straightforward model, we chose to implement 'stupid fall-back', a simple and commonly used technique, where if a sequence of words doesn't occur in the n-gram model, you assign it's probability to be a number (L) times the probability of the sequence in an n-1 gram model (recursively until 1-gram). To actually do this, we have to store all n-grams up to our decided max. Storing that much data past n = 5 isn't possible given our limited resources, so we used a pseudo 'sparse-matrix' dictionary to store up to a 7-gram model. Just to try and push things further, we tried to compress our keys in our 'sparse-matrix' and were able to go all the way up to a 18-gram model before running out of memory on a 16GB RAM machine.
While unfortunately this didn't have too large of an improvement over the 7-gram, we found the brute force compression solution to be interesting to implement, so we've included the 15-gram solution, which consumes around 10GB of RAM, which uncompressed was unrunnable on our hardware.
We do believe that given a much larger data set, this brute force approach would work pretty well. However, given the relatively small data set, it's difficult to find a good compromise in stupid fall-back L values which gives believable results without repeating the original data set.

In [15]:
```
all_unique_words = word_punc_df['word'].unique()
```

In [16]:
```python
n = 15

def compress(t):
    return zlib.compress(cPickle.dumps(t))

def decompress(t):
    return cPickle.loads(zlib.decompress(t))

sparseMatrixLike = defaultdict(np.float16)
sparseMatrixLike[compress(tuple([None] * n))] = 0.0

words_in_order = word_punc_df['word'].to_list()

prevData = []
prevData.append(None)
for i in range(n):
    prevData.append(words_in_order[i])


for word in words_in_order[n-1:]:
    prevData.append(word)
    prevData.pop(0)
    args = tuple(list([prevData[x] for x in range(0,n)]))
    for i in range(n):
        sparseMatrixLike[compress(args)] +=1
        l = list(args)[1:]
        l.append(None)
        args = tuple(l)
```

In [17]:
```python
divisor = len(words_in_order) - (n-1)
for k, v in sparseMatrixLike.items():
    sparseMatrixLike[k] = sparseMatrixLike[k] / (divisor)
```

In [49]:
```
sparseLike = sparseMatrixLike
def stupid_fall_back_fill(words, word_list):
    global sparseLike
    global n
    for word in word_list:
        sparseLike[compress(tuple(words + [word]))] = stupid_fall_back(tuple(w
ords + [word]), n-1)

def stupid_fall_back(words, index):
    global sparseLike
    if compress(words) in sparseLike:
        return sparseLike[compress(words)]
    l = list(words)[1:]
    l.append(None)
    words = tuple(l)
    return 0.3 * stupid_fall_back(words, index - 1)

message = ['to', 'illustrate', 'the', 'properties', 'of', 'our', 'model', ',',
'we', 'compared', 'its', 'accuracy', 'to', 'the']

import random
for i in range(100):
    print(message[0], end=' ')

    #Not checking all words possible just to finish running in a reasonable ti
meframe
    word_list = [x for x in all_unique_words if (compress((message[n-3],messag
e[n-2],x,None,None,None,None,None,None,None,None,None,None,None,None)) in spar
seLike)]

    if len(word_list) < 2:
        word_list = [x for x in all_unique_words if (compress((message[n-2],x,
None,None,None,None,None,None,None,None,None,None,None,None,None)) in sparseLi
ke)]
        if len(word_list) < 2:
            word_list = [x for x in all_unique_words if (compress((x,None,None
,None,None,None,None,None,None,None,None,None,None,None,None)) in sparseLike)]

    stupid_fall_back_fill(message, word_list)

    maxVal = 0.0
    for sel in word_list:
        maxVal += sparseLike[compress(tuple(message + [sel]))]
    x = random.uniform(0, 1) * maxVal

    looped = True
    for sel in word_list:
        x -= sparseLike[compress(tuple(message + [sel]))]
        if x < 0:
            message.append(sel)
            message.pop(0)
            looped = False
            break
    if looped == True:
        print(message)
        print(maxVal)
        print(word_list)
        break

while len(message) > 0:
    print(message[0], end=' ')
    message.pop(0)
```

```
to illustrate the properties of our model , we compared its accuracy to the f
eature ensemble size oracle , however they are associated with layer by vecto
r ` * , defined : ` qt de and castaing kernel matrix , not full rank rn it ca
n more easily identified by the recent success of dual methods in regularized
learning problems , we systematically build sparse duality theory and propose
an iht style algorithm along with its stochastic variant for dual optimizatio
n . overview of our contribution . the problem lies in the appendices . , 201
5 ) first propose an architecture designed for finite observation space ) , t
his coreset with non convex dm
```

Problem 3

Data Pre-Processing

In [19]:
```
train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")
```

In [20]:
```
test.head()
```

Out[20]:

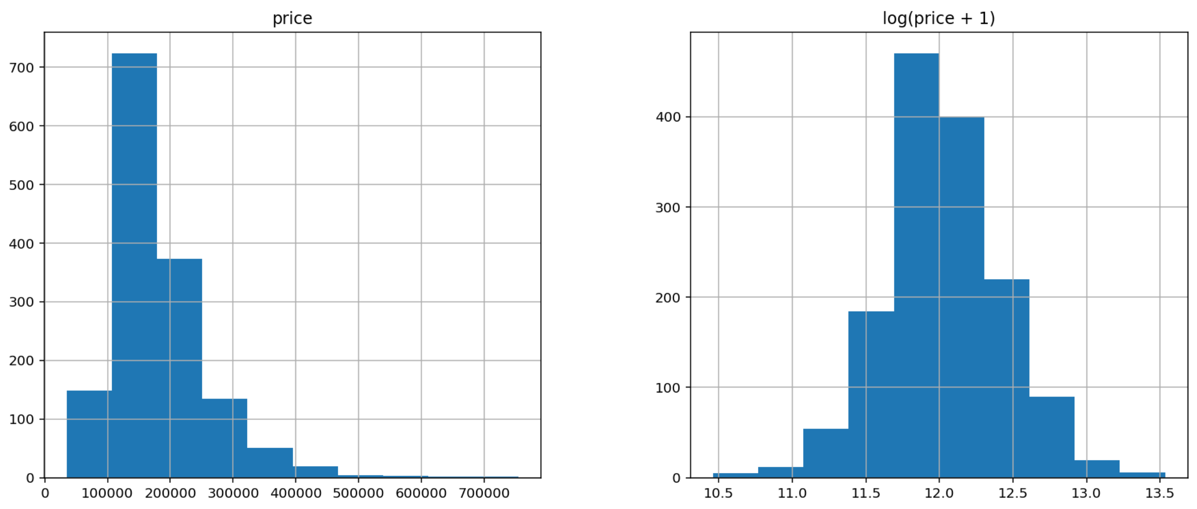
	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS

5 rows × 80 columns

In [21]:
```
all_data = pd.concat((train.loc[:,'MSSubClass':'SaleCondition'],
                      test.loc[:,'MSSubClass':'SaleCondition']))
```

In [22]:
```python
matplotlib.rcParams['figure.figsize'] = (15.0, 6.0)
prices = pd.DataFrame({"price":train["SalePrice"], "log(price + 1)":np.log1p(t
rain["SalePrice"])})
prices.hist()
```

Out[22]:
```
array([[<AxesSubplot:title={'center':'price'}>,
        <AxesSubplot:title={'center':'log(price + 1)'}>]], dtype=object)
```



In [23]:
```python
#log transform the target:
train["SalePrice"] = np.log1p(train["SalePrice"])

#log transform skewed numeric features:
numeric_feats = all_data.dtypes[all_data.dtypes != "object"].index

skewed_feats = train[numeric_feats].apply(lambda x: skew(x.dropna())) #compute
skewness
skewed_feats = skewed_feats[skewed_feats > 0.75]
skewed_feats = skewed_feats.index

all_data[skewed_feats] = np.log1p(all_data[skewed_feats])
```

In [24]:
```python
all_data = pd.get_dummies(all_data)
```

In [25]:
```python
#filling NA's with the mean of the column:
all_data = all_data.fillna(all_data.mean())
```

In [26]:
```python
#creating matrices for sklearn:
X_train = all_data[:train.shape[0]]
X_test = all_data[train.shape[0]:]
y = train.SalePrice
```

Ridge Regression

In [27]:
```
def rmse_cv(model):
    rmse= np.sqrt(-cross_val_score(model, X_train, y, scoring="neg_mean_square
d_error", cv = 5))
    return(rmse)
```

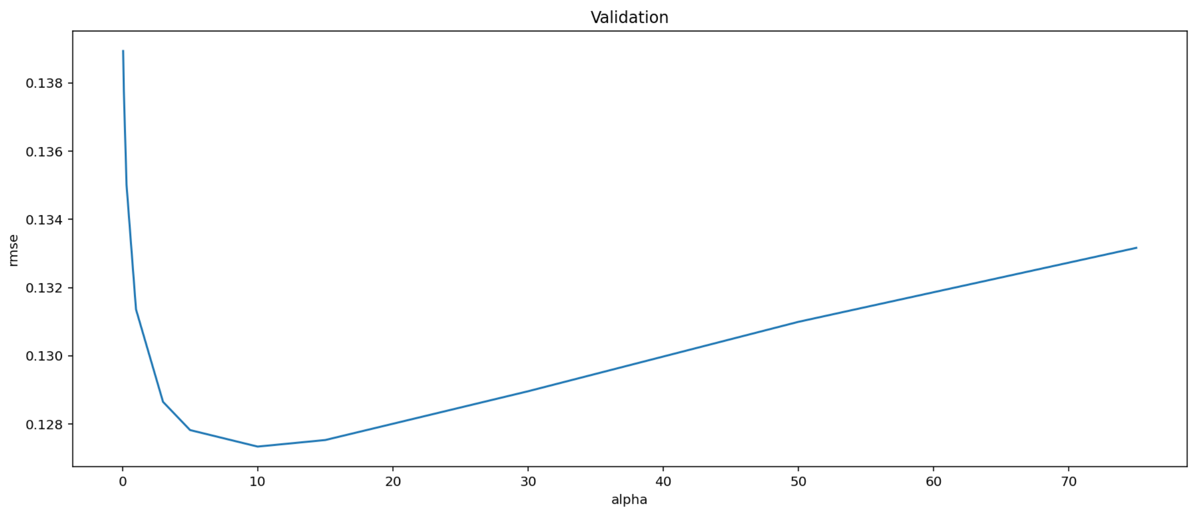
In [28]:
```
model_ridge = Ridge()
```

In [29]:
```
alphas = [0.1]
cv_ridge = [rmse_cv(Ridge(alpha = alpha)).mean() for alpha in alphas]
print("rmse for alpha = 0.1:", cv_ridge)
```

```
rmse for alpha = 0.1: [0.13777538277187829]
```

In [30]:
```
# optimize alpha value
alphas = [0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 50, 75]
cv_ridge = [rmse_cv(Ridge(alpha = alpha)).mean() for alpha in alphas]
cv_ridge = pd.Series(cv_ridge, index = alphas)
cv_ridge.plot(title = "Validation")
plt.xlabel("alpha")
plt.ylabel("rmse")

optimalAlpha = cv_ridge[cv_ridge == cv_ridge.min()].index[0]
print("Optimal alpha:",optimalAlpha)
print("rmse: ", cv_ridge.min())
rmse1 = cv_ridge.min()
```

```
Optimal alpha: 10.0
rmse:  0.12733734668670776
```



In [31]:
```
# train model
ridge = Ridge(alpha=optimalAlpha)
ridge.fit(X_train, y)
yPredict = ridge.predict(X_test)
yPredict = np.expm1(yPredict)
```

LASSO Regression

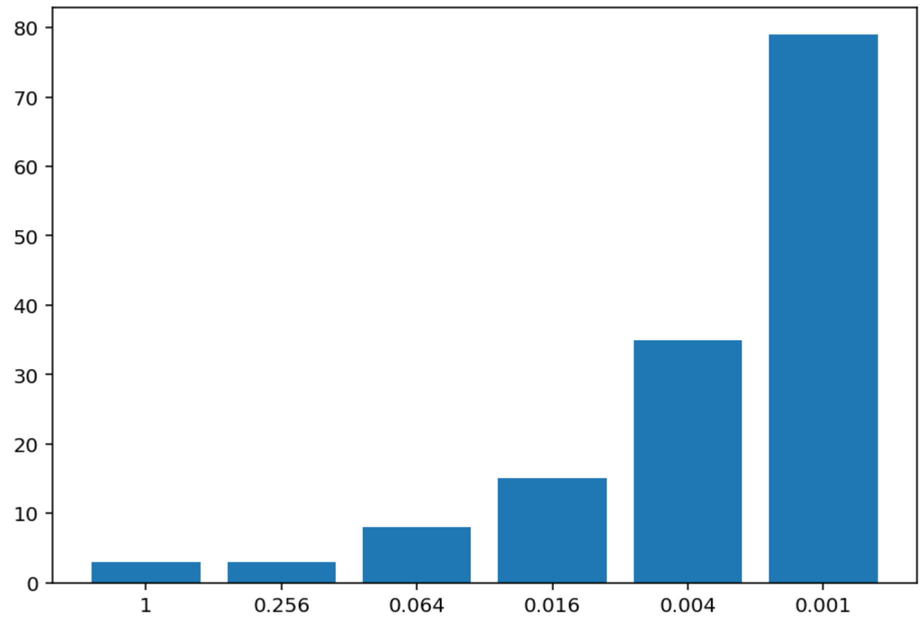
In [61]:
```
model_lasso = LassoCV(alphas = [1, 0.1, 0.001, 0.0005]).fit(X_train, y)

yPredict_ls = model_lasso.predict(X_test)
yPredict_ls = np.expm1(yPredict_ls)

rmse_cv(model_lasso).mean()
```

Out[61]:
```
0.1225673588504812
```

In [35]:
```
coef = pd.Series(model_lasso.coef_, index = X_train.columns)

print("Lasso kept " + str(sum(coef != 0)) + " fields and eliminated " + str(su
m(coef==0)) + " fields")
```

```
Lasso kept 110 fields and eliminated 178 fields
```

In [57]:
```
model_lasso_vary = []
alphas_test = [1, 0.256, 0.064, 0.016, 0.004, 0.001]
for alpha_test in alphas_test:
    model_lasso_test = Lasso(alpha=alpha_test).fit(X_train,y)
    model_lasso_vary.append(model_lasso_test)

non_zero_l0 = [sum(pd.Series(x.coef_, index = X_train.columns) != 0) for x in
model_lasso_vary]

non_zero_graph = plt.figure().add_axes([0,0,1,1]).bar([str(x) for x in alphas_
test], non_zero_l0)
plt.show()
```



Ensembling

In [68]:
```
# add output as feature
X_train_stack = X_train
Predicted_Y = pd.DataFrame({"Predicted Y":yPredict})
Predicted_Y = Predicted_Y.append(Predicted_Y.loc[0], yPredict.mean())
Predicted_Y_lasso = pd.DataFrame({"Predicted Y Lasso":yPredict_ls})
Predicted_Y_lasso = Predicted_Y_lasso.append(Predicted_Y_lasso.loc[0], yPredic
t_ls.mean())
X_train_stack = X_train_stack.assign(Predicted_Y = Predicted_Y.values)
X_train_stack = X_train_stack.assign(Predicted_Y_lasso = Predicted_Y_lasso.val
ues)
X_train_stack
```

Out[68]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd
0	4.110874	4.189655	9.042040	7	5	2003	2003
1	3.044522	4.394449	9.169623	6	8	1976	1976
2	4.110874	4.234107	9.328212	7	5	2001	2002
3	4.262680	4.110874	9.164401	7	5	1915	1970
4	4.110874	4.442651	9.565284	8	5	2000	2000
...	...	...	...	...	...	...	...
1455	4.110874	4.143135	8.976894	6	5	1999	2000
1456	3.044522	4.454347	9.486152	6	6	1978	1988
1457	4.262680	4.204693	9.109746	7	9	1941	2006
1458	3.044522	4.234107	9.181735	5	6	1950	1996
1459	3.044522	4.330733	9.204121	5	6	1965	1965

1460 rows × 290 columns

In [69]:
```
# optimize alpha value for stacked model

def rmse_cv_stacked(model):
    rmse= np.sqrt(-cross_val_score(model, X_train_stack, y, scoring="neg_mean_
squared_error", cv = 5))
    return(rmse)

alphas = [0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 50, 75]
cv_ridge = [rmse_cv_stacked(Ridge(alpha = alpha)).mean() for alpha in alphas]
cv_ridge = pd.Series(cv_ridge, index = alphas)
optimalAlpha = cv_ridge[cv_ridge == cv_ridge.min()].index[0]

print("Optimal alpha:",optimalAlpha)
print("rmse2: ", cv_ridge.min())
rmse2 = cv_ridge.min()

# train stacked model
ridge2 = Ridge(alpha=optimalAlpha)
ridge2.fit(X_train_stack, y)
yPredict2 = ridge.predict(X_test)
yPredict2 = np.expm1(yPredict2)

# stacked ridge model vs original model?
print("Is rmse2 larger than rmse1?", rmse2 > rmse1)
```

```
Optimal alpha: 10.0
rmse2:  0.12746505029595684
Is rmse2 larger than rmse1? True
```

XGBoost Regression

Finding the best hyperpararameters for XGBoost Regression using GridSearchCV. Originally these dictionaries had a lot more values, but they were condensed through trial and error.

In [ ]:
```
xgb_model = xgb.XGBRegressor()

param_grid = {
    'learning_rate': [0.15],
    'max_depth': [3],
    'min_child_weight': [1],
    'gamma': [0.1],
    'colsample_bytree': [0.4],
    'n_estimators': [325]}

MSE = make_scorer(mean_squared_error, greater_is_better=False)
model = GridSearchCV(estimator=xgb_model, param_grid=param_grid, n_jobs=-1, cv
=3, scoring=MSE, verbose=2)
model.fit(X_train, y)
print('XGBoost Regression...')
print('Best Params:', model.best_params_)
print('Best CV Score:', -model.best_score_)
```

In [38]:
```
params = {'colsample_bytree': 0.4, 'gamma': 0.1, 'learning_rate': 0.15, 'max_d
epth': 3, 'min_child_weight': 1, 'n_estimators': 325}
model_xgb = xgb.XGBRegressor(**params)
```

Random Forest Regression

Finding the best hyperpararameters for Random Forest Regression using GridSearchCV. Originally these dictionaries had a lot more values, but they were condensed through trial and error.

In [ ]:
```
rfr = RandomForestRegressor(verbose=0)

param_grid = {
    'bootstrap': [True],
    'max_depth': [96],
    'max_features': ['auto'],
    'min_samples_leaf': [2],
    'min_samples_split': [2],
    'n_estimators': [2070]}

MSE = make_scorer(mean_squared_error, greater_is_better=False)
model = GridSearchCV(estimator=rfr, param_grid=param_grid, n_jobs=-1, cv=3, sc
oring=MSE, verbose=2)
model.fit(X_train, y)
print('Random forest regression...')
print('Best Params:', model.best_params_)
print('Best CV Score:', -model.best_score_)
```

In [39]:
```
params = {'bootstrap': True, 'max_depth': 96, 'max_features': 'auto', 'min_sam
ples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 2070}
model_rfr = RandomForestRegressor(**params)
```

SVR

We used GridSearchCV to tune the hyperparameters for the SVR model. Originally, the list of possible parameter values was quite extensive, but eventually got reduced to what is shown below based on trial and error.

```
In [ ]: optimalSVR = GridSearchCV(estimator=SVR(kernel='rbf'),
                           param_grid = {
                               'C': [0.1, 1, 10, 100, 10000, 15000],
                               'epsilon': [0.01, 0.012, 0.013, 0.0135],
                               'gamma': [8e-05,9e-05,9.5e-05,0.0001]
                           },
                           cv = 8,
                           scoring = 'neg_mean_squared_error',
                           verbose = 0,
                           n_jobs = -1)

        optimalSVR.fit(X_train, y)
```

```
In [ ]: print("Optimal Parameters:", optimalSVR.best_params_)
        print("MSE: ", -optimalSVR.best_score_)
        print("RMSE: ", np.sqrt(-optimalSVR.best_score_))
        print("Standard Dev:", optimalSVR.cv_results_['std_test_score'][optimalSVR.bes
        t_index_])
```

```
In [40]: svr_optimal = {'C': 100, 'epsilon': 0.0135, 'gamma': 8e-05}
         model_svr = SVR(kernel='rbf', **svr_optimal)
         model_svr.fit(X_train, y)

Out[40]: SVR(C=100, epsilon=0.0135, gamma=8e-05)
```

GBM Regression

```
In [ ]: model_lgbm = LGBMRegressor(boosting_type='gbdt', objective='regression', metri
        c = 'rmse')

        model_lgbm.fit(X_train, y)

        rmse_cv(model_lgbm).mean()

        MSE = make_scorer(mean_squared_error, greater_is_better=False)

        param_grid_lgbm = {
            'num_leaves' : np.arange(-1,15,1),
            'max_depth' : np.arange(-1, 6, 1),
            'learning_rate' : np.arange(0.03,0.08,0.01),
            'n_estimators' : np.arange(400,450,10)
        }

        model_lgbm_hyper = GridSearchCV(estimator=model_lgbm, param_grid=param_grid_lg
        bm, n_jobs=-1, cv=4, scoring=MSE)

        model_lgbm_hyper.fit(X_train,y)

        score = -model_lgbm_hyper.best_score_

        print('Best Params:\n', model_lgbm_hyper.best_params_)
        print('Best CV Score:', score)
```

```
In [41]: saved_best = {'learning_rate': 0.060000000000000005, 'max_depth': -1, 'n_estim
         ators': 420, 'num_leaves': 9}
         model_lgbm_set = LGBMRegressor(boosting_type='gbdt', objective='regression', m
         etric = 'rmse', **saved_best)
         model_lgbm_set.fit(X_train,y)

         rmse_cv(model_lgbm_set).mean()

Out[41]: 0.12782947906259498
```

Stacking Models

Finally, we compile our models using a stacking regressor and check which final estimator gives the least error using rmse. This was done through trial and error seeing which rmse value was the lowest for each final regressor.

RFR Meta Model rmse: 0.12510261384031024

XGB Meta Model rmse: 0.12492697684309169

Ridge Meta Model rmse: 0.11891085433887438

LGBM Meta Model rmse: 0.12746463317549858

Lasso Meta Model rmse: 0.11906390504408422

SVR Meta Model rmse: 0.11950418291006988

```
In [ ]: estimators_stack = [('svr', model_svr),
                           ('rfr', model_rfr),
                            ('xgb', model_xgb),
                            ('lasso', model_lasso),
                            ('ridge', ridge),
                            ('gbm', model_lgbm_set)]
        big_stacker = StackingRegressor(n_jobs = -1, estimators=estimators_stack, fina
        l_estimator=model_lasso)
        big_stacker.fit(X_train, y)
        rmse_cv(big_stacker).mean()
```

```
In [ ]: output = np.expm1(big_stacker.predict(X_test))
        out_db = pd.DataFrame()
        out_db['Id'] = test['Id']
        out_db['SalePrice'] = output
        out_db.tail()
```

```
In [ ]: out_db.to_csv('bigstacker.csv',index=False)
```

We found that the final scoring for the following meta-models was the lowest

- SVR with 0.12085 RMSE
- Ridge with 0.11968 RMSE
- LASSO with 0.11913 RMSE

Because of these RMSE values, we produced our results using a LASSO meta-model

Kaggle Team

Team Name: The Big Stackers
Test (Public) Score: 0.11913