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Spooky Author testing

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In our project we've decided to use our dataset from the Kaggle Spooky Author Identification competition[0]

Here we're given a large dataset and testing set of data for comparing work done by different horror authors, and our goal will be to tell if we can differentiate the authors from one another just based off analyzing different words and styles they use.

Initially we'll test the idea with linear regression, which we expect to get poor rates for, and then we'll use different techniques to read in the data, such as changing the number of senteces we read in at a time to improve accuracy, or trying new tequniques not used in class.

```
% For this project you may want to have matlabNLP installed for some
% versions.

% read in file, set training data to td
filename = 'train.csv';
file = readtable(filename);
td = table2array(file);

% Shorten td to reasonable size, can remove later
% td = td(1:10000,:);

[n,m] = size(td);

eap_occurance = 0;
hpl_occurance = 0;
mws_occurance = 0;
for i = 1:n
    if strcmp(td(i,3),'EAP')
        eap_occurance = eap_occurance + 1;
    elseif strcmp(td(i,3),'HPL')
        hpl_occurance = hpl_occurance + 1;
    elseif strcmp(td(i,3),'MWS')
        mws_occurance = mws_occurance + 1;
    else
        fprinf('Didnt work on line %i\n', i);
    end
end

% This total should now equal n
if (n == (eap_occurance + hpl_occurance + mws_occurance))
```

```
    fprintf('number of names categorized correctly.\n');
end
```

number of names categorized correctly.

Categorizing their text

Now that we have the size of each required array, we can enter each word into an array for the three authors, and then compare them directly that way.

Recall our end game is we want to calculate the weights, so w = X\y, and X will be a matrix of the given words/sentences, while y will be the estimate for each author.

Another way to write this is that X would be the number of times a word comes up in a sentence, so that times a weight would be the likelihood of it being a specific author.

author = of word per sentence * it's an author

So we would see X as perhapse a large matrix, where each row is a different sentence, each column is the rate at which a word shows up, and each row in the w is the weight for the corrisponding word column in the X matrix. From here we produce a y matrix, this y matrix will be a column with a height equal to the number of sentences, where each sentence is a weight.

Additionally I'll note that the words chosen are to some extent arbitrary. We've been basing words by each author off of other research into each author based off of word use frequency. Additionally we've been avoiding nouns and names as even though some authors use them more often than others it can still throw off the data significantly. Lastly after taking this into account, we've use/thrown out words with high or low weights, where high weights suggest it's more relevant than a low weight.

MWS [1] ELP [2] HPL [3][4]

```
% List of words we've chosen, we've limited the size so that the
 matrix
% multiplication may still run quickly.
words =
 {'ascertain','lay','my','surcingle','hand','thus','to','nor','subject','suffer','
[wn,wm] = size(words);

data = zeros(wm,n);
% Need to collect word data for 100 sentences
for i = 1:wm
    for j = 1:n
        wordLoc = strfind(td{j,2}, words{i});
        data(i,j) = length(wordLoc);
    end
end

% Flipping matrix as it was accidentally built upsidown.
X = transpose(data);

% Now we must build the y matrix, it would be best to incorporate this
 in
% with the above algo later on, though the O(N^2) time complexity
 remains
% the same.
y = zeros(n,1);
```

```
for i = 1:n
    if (length(strfind(td{i,3}, 'EAP')) >= 1)
        y(i,1) = +1;
    else
        y(i,1) = -1;
    end
end

% So we can build the weight setup as
w = X\y;

% And then we'll test it for EAP in the next 10 matricies

Warning: Rank deficient, rank = 64, tol =  1.942057e-09.
```

Testing on small sample set

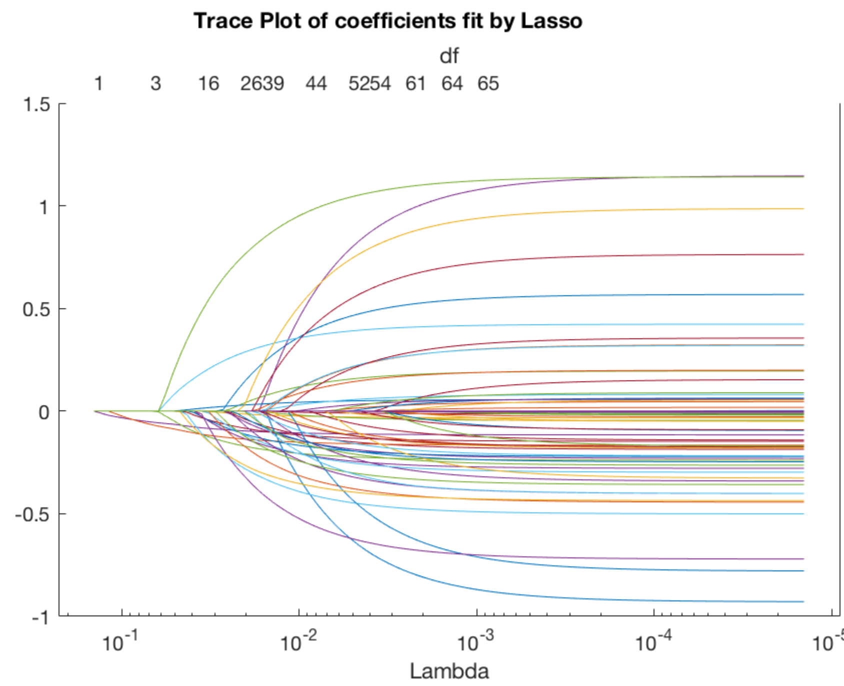
```
test = table2array(file);
test = test(10000:10999,:);
n = length(test);

% We need to set up the environment by copying and pasting the code
 from
% above but with a test
X_test = zeros(wm,n);
for i = 1:wm
    for j = 1:n
        wordLoc = strfind(test{j,2}, words{i});
        X_test(i,j) = length(wordLoc);
    end
end

X_test = transpose(X_test);

% So the predicted vector is
y_hat = X_test*w;

% And we can compare this to the expected output, so
y_expected = zeros(n,1);
for i = 1:n
    if (length(strfind(test{i,3}, 'EAP')) >= 1)
        y_expected(i) = +1;
    else
        y_expected(i) = -1;
    end
end

% Now we test it to see easily how many were right
vals = zeros(20,2);
for i = 1:n
    vals(i,1) = y_hat(i);
    vals(i,2) = y_expected(i);
end
```

```
% sum up right answers
sum = 0;
for i = 1:n
    if (sign(vals(i,1)) == sign(vals(i,2)))
        sum = sum + 1;
        vals(i,1);
        vals(i,2);
    end
end

fprintf('There were %i right answers out of %i, which equals a %2.2d
 correct percentage.\n', sum, n, (sum/n)*100);
```

There were 596 right answers out of 1000, which equals a 5.96e+01 correct percentage.

Lasso use

```
% For comparison here is the result of the built in LASSO regression
 on the
% data
[B, FitInto] = lasso(X,y);
lassoPlot(B,FitInto,'PlotType','Lambda','XScale','log');


%The plot shows the nonzero coefficients in the regression for
 various values of the Lambda regularization parameter. Larger
 values of Lambda appear on the left side of the graph, meaning more
 regularization, resulting in fewer nonzero regression coefficients.
%The dashed vertical lines represent the Lambda value with minimal
 mean squared error (on the right), and the Lambda value with minimal
 mean squared error plus one standard deviation. This latter value is
 a recommended setting for Lambda. These lines appear only when you
 perform cross validation. Cross validate by setting the 'CV' name-
value pair. This example uses 10-fold cross validation.
%The upper part of the plot shows the degrees of freedom (df), meaning
 the number of nonzero coefficients in the regression, as a function
 of Lambda. On the left, the large value of Lambda causes all but one
 coefficient to be 0. On the right all five coefficients are nonzero,
 though the plot shows only two clearly. The other three coefficients
 are so small that you cannot visually distinguish them from 0.
%For small values of Lambda (toward the right in the plot), the
 coefficient values are close to the least-squares estimate.
```



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