Word Embeddings

- Dense representations

Outline

- What is a Word Embedding?
- Loading a Pre-Trained Word Embedding from GloVe
- Visualizing the Word Embedding
- Using Word Embeddings for Sentiment Analysis
- Training and Evaluating the Sentiment Classifier
- Computing Sentiment Scores
- Sentiment by Location
- Train WordEmbedding

What is a Word Embedding?

- Word embedding is simply a vector representation of a word, with the vector containing real numbers. Since languages typically contain at least tens of thousands of words, simple binary word vectors can become impractical due to high number of dimensions. Word embeddings solve this problem by providing dense representations of words in a low-dimensional vector space.

- Since mid-2010s, word embeddings have being applied to neural network-based NLP tasks. Among the well-known embeddings are word2vec (Google), GloVe (Stanford) and FastText (Facebook).

What is a Word Embedding?

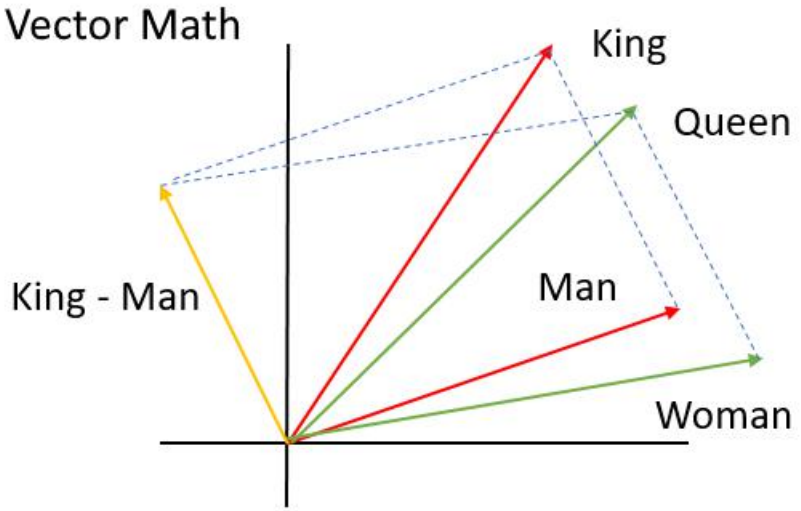
- Word embedding "embeds" words into a vector space model based on how often a word appears close to other words. Done at an internet scale, you can attempt to capture the semantics of the words in the vectors, so that similar words have similar vectors.

- One very famous example of how word embeddings can represent such relationship is that you can do a vector computation like this:

$$king - man + woman \approx queen$$

What is a Word Embedding?

- "queen" is like "king" except that it is a woman, rather than a man! How cool is that? This kind of magic has become possible thanks to vast availability of raw text data on the internet, greater computing capability that can process it, and advances in artificial neural networks, such as deep learning.



Ingredients

In this example, we will use a pre-trained word embedding from GloVe.

- Download a free trial version of Text Analytics Toolbox (MATLAB and Statistics and Machine Learning Toolbox R2017b or later are also required).
- Download the pre-trained model glove.6B.300d.txt (6 billion tokens, 400K vocabulary, 300 dimensions) from GloVe.
- Download the sentiment lexicon from University of Illinois at Chicago
- Download the data from the Boston Airbnb Open Data page on Kaggle
- Download my custom function load_lexicon.m and class sentiment.m as well as the raster map of Boston

Please extract the content from the archive files into your current folder.

Loading a Pre-Trained Word Embedding from GloVe

- You can use the function readWordEmbedding in Text Analytics Toolbox to read pre-trained word embeddings. To see a word vector, use word2vec to get the vector representation of a given word. Because the dimension for this embedding is 300, we get a vector of 300 elements for each word.

```
filename = "glove.6B.300d";
if exist(filename + '.mat', 'file') ~= 2
    emb = readWordEmbedding(filename + '.txt');
    save(filename + '.mat', 'emb', '-v7.3');
else
    load(filename + '.mat')
end
```

Loading a Pre-Trained Word Embedding from GloVe

```
v_king = word2vec(emb,'king')';

whos v_king

  Name        Size            Bytes  Class     Attributes

  v_king      300x1            1200  single
```

Vector Math Example

Let's try the vector math! Here is another famous example:

$$paris - france + poland \approx warsaw$$

Apparently, the vector subtraction "paris - france" encodes the concept of "capital" and if you add "poland", you get "warsaw".

Vector Math Example

- Let's try it with MATLAB. word2vec returns vectors for given words in the word embedding, and vec2word finds the closest words to the vectors in the word embedding.

```
v_paris = word2vec(emb,'paris');
v_france = word2vec(emb,'france');
v_poland = word2vec(emb,'poland');
vec2word(emb, v_paris - v_france +  v_poland)
ans =
    "warsaw"
```

Visualizing the Word Embedding

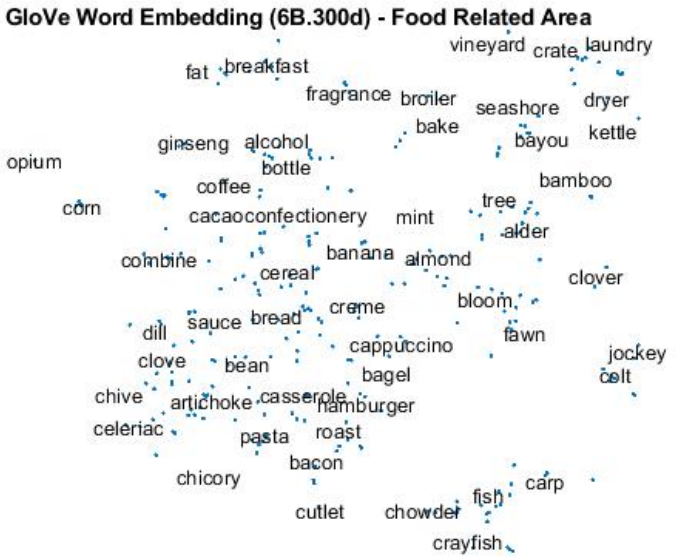
- We would like to visualize this word embedding using textscatter plot, but it is hard to visualize it if all 400,000 words from the word embedding are included.
- We found a list of 4,000 English nouns. Let's use those words only and reduce the dimensions from 300 to 2 using tsne (t-Distributed Stochastic Neighbor Embedding) for dimensionality reduction. To make it easier to see words, we zoomed into a specific area of the plot that contains food related-words. You can see that related words are placed close together.

Visualizing the Word Embedding

```
if exist('nouns.mat','file') ~= 2
    url = 'http://www.desiquintans.com/downloads/nounlist/nounlist.txt';
    nouns = webread(url);
    nouns = split(nouns);
    save('nouns.mat','nouns');
else
    load('nouns.mat')
end
nouns(~ismember(nouns,emb.Vocabulary)) = [];
vec = word2vec(emb,nouns);
rng('default'); % for reproducibility
xy = tsne(vec);
```

Visualizing the Word Embedding

```
figure
textscatter(xy,nouns)
title('GloVe Word Embedding (6B.300d) - Food Related Area')
axis([-35 -10 -36 -14]);
set(gca,'clipping','off')
axis off
```



Using Word Embeddings for Sentiment Analysis

- For a practical application of word embeddings, let's consider sentiment analysis. We would typically take advantage of pre-existing sentiment lexicons such as this one from the University of Illinois at Chicago. It comes with 2,006 positive words and 4,783 negative words. Let's load the lexicon using the custom function load_lexicon.

- If we just rely on the available words in the lexicon, we can only score sentiment for 6,789 words. One idea to expand on this is to use the word embedding to find words that are close to these sentiment words.

Using Word Embeddings for Sentiment Analysis

```
pos = load_lexicon('positive-words.txt');
neg = load_lexicon('negative-words.txt');
[length(pos) length(neg)]

ans =
        2006        4783
```

Word Embeddings Meet Machine Learning

- What if we use word vectors as the training data to develop a classifier that can score all words in the 400,000-word embedding? We can take advantage of the fact that related words are close together in word embeddings to do this. Let's make a sentiment classifier that takes advantage of the vectors from the word embedding.

- As the first step, we will get vectors from the word embedding for words in the lexicon to create a matrix of predictors with 300 columns, and then use positive or negative sentiment labels as the response variable. Here is the preview of the word, response variable and the first 7 predictor variables out of 300.

```
% Drop words not in the embedding
pos = pos(ismember(pos,emb.Vocabulary));
neg = neg(ismember(neg,emb.Vocabulary));

% Get corresponding word vectors
v_pos = word2vec(emb,pos);
v_neg = word2vec(emb,neg);

% Initialize the table and add the data
data = table;
data.word = [pos;neg];
pred = [v_pos;v_neg];
data = [data array2table(pred)];
data.resp = zeros(height(data),1);
data.resp(1:length(pos)) = 1;

% Preview the table
head(data(:,[1,end,2:8 ]))
```

ans =

8×9 table

word	resp	pred1	pred2	pred3	pred4	pred5	pred6	pred7
"abound"	1	0.081981	-0.27295	0.32238	0.19932	0.099266	0.60253	0.18819
"abounds"	1	-0.037126	0.085212	0.26952	0.20927	-0.014547	0.52336	0.11287
"abundance"	1	-0.038408	0.076613	-0.094277	-0.10652	-0.43257	0.74405	0.41298
"abundant"	1	-0.29317	-0.068101	-0.44659	-0.31563	-0.13791	0.44888	0.31894
"accessible"	1	-0.45096	-0.46794	0.11761	-0.70256	0.19879	0.44775	0.26262
"acclaim"	1	0.07426	-0.11164	0.3615	-0.4499	-0.0061991	0.44146	-0.0067972
"acclaimed"	1	0.69129	0.04812	0.29267	0.1242	0.083869	0.25791	-0.5444
"acclamation"	1	-0.026593	-0.60759	-0.15785	0.36048	-0.45289	0.0092178	0.074671

Prepare Data for Machine Learning

- Let's partition the data into a training set and holdout set for performance evaluation. The holdout set contains 30% of the available data.

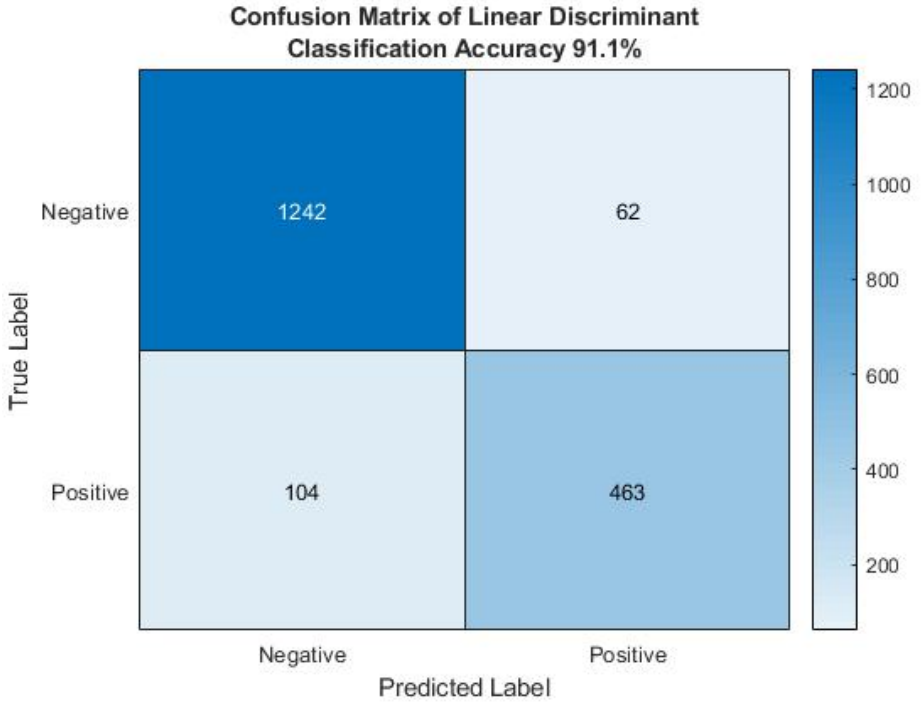
```
rng('default') % for reproducibility
c = cvpartition(data.resp,'Holdout',0.3);
train = data(training(c),2:end);
Xtest = data(test(c),2:end-1);
Ytest = data.resp(test(c));
Ltest = data(test(c),1);
Ltest.label = Ytest;
```

Training and Evaluating the Sentiment Classifier

- We want to build a classifier that can separate positive words and negative words in the vector space defined by the word embedding. For a quick performance evaluation, I chose the fast and easy linear discriminant among possible machine learning algorithms.

- Here is the confusion matrix of this model. The result was 91.1% classification accuracy.

```
% Train model
mdl = fitcdiscr(train,'resp');

% Predict on test data
Ypred = predict(mdl,Xtest);
cf = confusionmat(Ytest,Ypred);

% Display results
figure
vals = {'Negative','Positive'};
heatmap(vals,vals,cf);
xlabel('Predicted Label')
ylabel('True Label')
title({'Confusion Matrix of Linear Discriminant'; ...
    sprintf('Classification Accuracy %.1f%%', ...
    sum(cf(logical(eye(2))))/sum(sum(cf))*100)})
```



Training and Evaluating the Sentiment Classifier

- Let's check the predicted sentiment score against the actual label. The custom class sentiment uses the linear discriminant model to score sentiment.
- The scoreWords method of the class scores words. A positive score represents positive sentiment, and a negative score is negative. Now we can use 400,000 words to score sentiment.

dbtype sentiment.m 18:26

```
18        function scores = scoreWords(obj,words)
19            %SCOREWORDS scores sentiment of words
20            vec = word2vec(obj.emb,words);         % word vectors
21            if size(vec,2) ~= obj.emb.Dimension     % check num cols
22                vec =  vec';                    % transpose as needed
23            end
24            [~,scores,~] = predict(obj.mdl,vec);    % get class probabilities
25            scores = scores(:,2) - scores(:,1);     % positive scores - negative scores
26        end
```

Training and Evaluating the Sentiment Classifier

Let's test this custom class. If the label is 0 and score is negative or the label is 1 and score is positive, then the model classified the word correctly. Otherwise, the word was misclassified.

Here is the table that shows 10 examples from the test set:

- the word
- its sentiment label (0 = negative, 1 = positive)
- its sentiment score (negative = negative, positive = positive)
- evaluation (true = correct, false = incorrect)

```
sent = sentiment(emb,mdl);
Ltest.score = sent.scoreWords(Ltest.word);
Ltest.eval = Ltest.score > 0 == Ltest.label;
disp(Ltest(randsample(height(Ltest),10),:))
```

word	label	score	eval
"fugitive"	0	-0.90731	true
"misfortune"	0	-0.98667	true
"outstanding"	1	0.99999	true
"reluctant"	0	-0.99694	true
"botch"	0	-0.99957	true
"carefree"	1	0.97568	true
"mesmerize"	1	0.4801	true
"slug"	0	-0.88944	true
"angel"	1	0.43419	true
"wheedle"	0	-0.98412	true

Training and Evaluating the Sentiment Classifier

- Now we need a way to score the sentiment of human-language text, rather than a single word. The scoreText method of the sentiment class averages the sentiment scores of each word in the text. This may not be the best way to do it, but it's a simple place to start.

dbtype sentiment.m 28:33

```
28          function score = scoreText(obj,text)
29              %SCORETEXT scores sentiment of text
30              tokens = split(lower(text));          % split text into tokens
31              scores = obj.scoreWords(tokens);      % get score for each token
32              score = mean(scores,'omitnan');       % average scores
33          end
```

Training and Evaluating the Sentiment Classifier

- Here are the sentiment scores on sentences given by the scoreText method - very positive, somewhat positive, and negative.

```
[sent.scoreText('this is fantastic') ...
sent.scoreText('this is okay') ...
sent.scoreText('this sucks')]
ans =
    0.91458     0.80663    -0.073585
```

Boston Airbnb Open Data

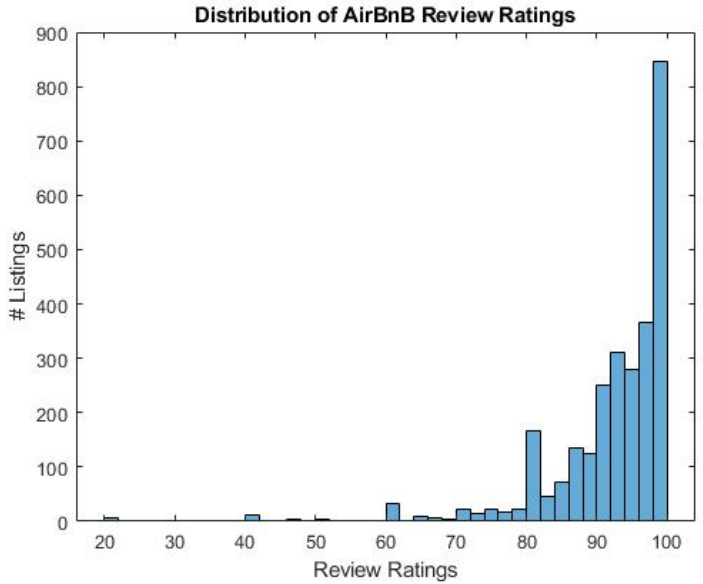
- Let's try this on review data from the Boston Airbnb Open Data page on Kaggle. First, we would like to see what people say in their reviews as a word cloud. Text Analytics Toolbox provides functionality to simplify text preprocessing workflows, such as tokenizedDocument which parses documents into an array of tokens, and bagOfWords that generates the term frequency count model (this can be used to build a machine learning model).
- The commented-out code will generate a word cloud. However, you can also generate word clouds using two-word phrases known as bigrams. You can generate bigrams with docfun, which operates on the array of tokens. You can also see that it is possible to generate trigrams and other n-grams by modifying the function handle.

```
opts = detectImportOptions('listings.csv');
l = readtable('listings.csv',opts);
reviews = readtable('reviews.csv');
comments = tokenizedDocument(reviews.comments);
comments = lower(comments);
comments = removeWords(comments,stopWords);
comments = removeShortWords(comments,2);
comments = erasePunctuation(comments);

% == uncomment to generate a word cloud ==
% bag = bagOfWords(comments);
% figure
% wordcloud(bag);
% title('AirBnB Review Word Cloud')

% Generate a Bigram Word Cloud
f = @(s)s(1:end-1) + " " + s(2:end);
bigrams = docfun(f,comments);
bag2 = bagOfWords(bigrams);
figure
wordcloud(bag2);
title('AirBnB Review Bigram Cloud')
```

Airbnb Review Ratings

- Review ratings are also available, but ratings are really skewed towards 100, meaning the vast majority of listings are just perfectly wonderful (really?). As this XCKD comic shows, we have the problem with online ratings with regards to review ratings. This is not very useful.

```
figure
histogram(l.review_scores_rating)
title('Distribution of AirBnB Review Ratings')
xlabel('Review Ratings')
ylabel('# Listings')
```

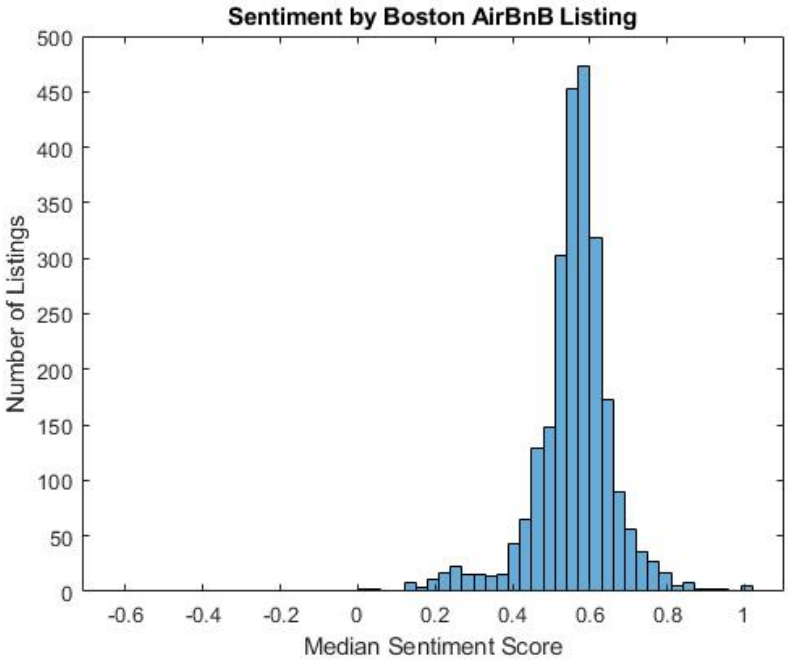


Computing Sentiment Scores

- Now let's score sentiment of Airbnb listing reviews instead. Since a listing can have number of reviews, we would use the median sentiment score per listing. The median sentiment scores in Boston are generally in the positive range, but it follows a normal distribution.

Computing Sentiment Scores

```
% Score the reviews
f = @(str) sent.scoreText(str);
reviews.sentiment = cellfun(f,reviews.comments);

% Calculate the median review score by listing
[G,listings] = findgroups(reviews(:,'listing_id'));
listings.sentiment = splitapply(@median, ...
    reviews.sentiment,G);

% Visualize the results
figure
histogram(listings.sentiment)
title('Sentiment by Boston AirBnB Listing')
xlabel('Median Sentiment Score')
ylabel('Number of Listings')
```



Sentiment by Location

The bigram cloud showed reviewers often commented on location and distance. You can use latitude and longitude of the listings to see where listings with very high or low sentiment scores are located. If you see clusters of high scores, perhaps they may indicate good locations to stay in.

```
% Join sentiment scores and listing info
joined = innerjoin( ...
    listings,l(:,{'id','latitude','longitude', ...
    'neighbourhood_cleansed'}), ...
    'LeftKeys','listing_id','RightKeys','id');
joined.Properties.VariableNames{end} = 'ngh';

% Discard listings with a NaN sentiment score
joined(isnan(joined.sentiment),:) = [];
```

Sentiment by Location

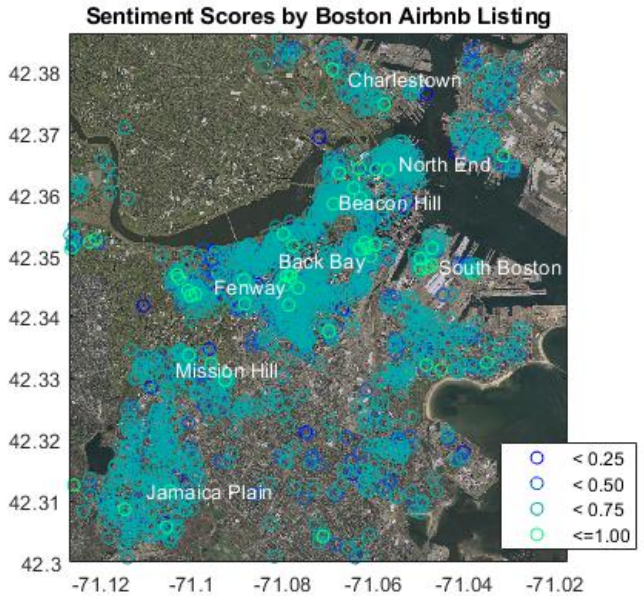
```
% Discretize the sentiment scores into buckets
joined.cat = discretize(joined.sentiment,0:0.25:1, ...
    'categorical',{'< 0.25','< 0.50','< 0.75','<=1.00'});

% Remove undefined categories
cats = categories(joined.cat);
joined(isundefined(joined.cat),:) = [];

% Variable for color
colorlist = winter(length(cats));
```

Sentiment by Location

```
% Generate the plot
latlim = [42.300 42.386];
lonlim = [-71.1270 -71.0174];
load boston_map.mat
figure
imagesc(lonlim,latlim, map)
hold on
gscatter(joined.longitude,joined.latitude,joined.cat,colorlist,'o')
hold off
dar = [1, cosd(mean(latlim)), 1];
daspect(dar)
set(gca,'ydir','normal');
axis([lonlim,latlim])
title('Sentiment Scores by Boston Airbnb Listing')
[g,ngh] = findgroups(joined(:,'ngh'));
ngh.Properties.VariableNames{end} = 'name';
ngh.lat = splitapply(@mean,joined.latitude,g);
ngh.lon = splitapply(@mean,joined.longitude,g);
```

Sentiment by Location

```
% Annotations
text(ngh.lon(2),ngh.lat(2),ngh.name(2),'Color','w')
text(ngh.lon(4),ngh.lat(4),ngh.name(4),'Color','w')
text(ngh.lon(6),ngh.lat(6),ngh.name(6),'Color','w')
text(ngh.lon(11),ngh.lat(11),ngh.name(11),'Color','w')
text(ngh.lon(13),ngh.lat(13),ngh.name(13),'Color','w')
text(ngh.lon(17),ngh.lat(17),ngh.name(17),'Color','w')
text(ngh.lon(18),ngh.lat(18),ngh.name(18),'Color','w')
text(ngh.lon(22),ngh.lat(22),ngh.name(22),'Color','w')
```



Summary

We focused on word embeddings and sentiment analysis as an example of new features available in Text Analytics Toolbox. Hopefully you saw that the toolbox makes advanced text processing techniques very accessible. You can do more with word embeddings besides sentiment analysis, and the toolbox offers many more features besides word embeddings, such as Latent Semantic Analysis or Latent Dirichlet Allocation.

Train Word Embedding

emb = trainWordEmbedding(filename)

- trains a word embedding using the training data stored in the text file filename. The file is a collection of documents stored in UTF-8 with one document per line and words separated by whitespace.

Train Word Embedding from File

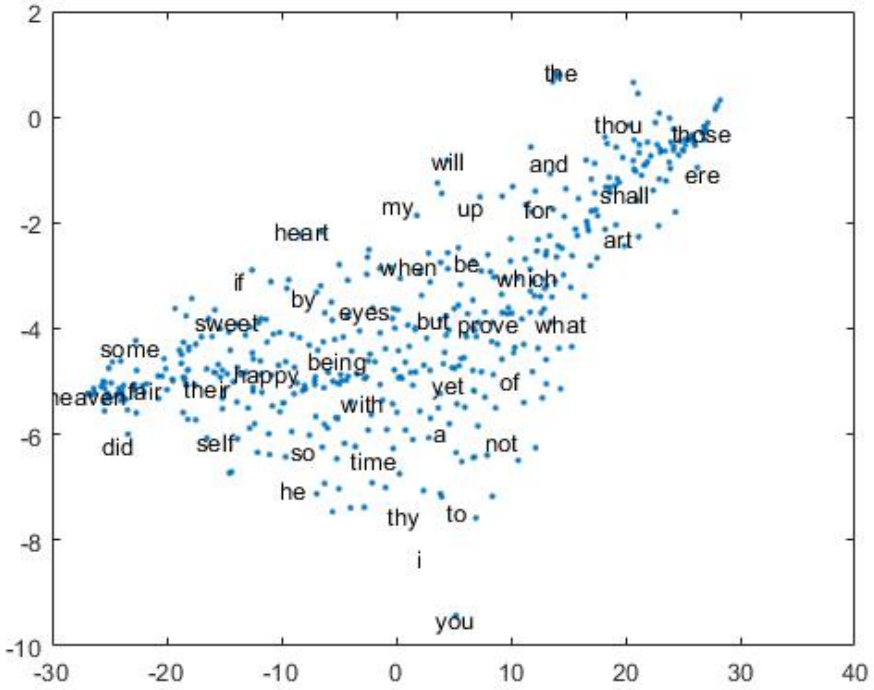
- Train a word embedding of dimension 100 using the example text file exampleSonnetsDocuments.txt. This file contains preprocessed versions of Shakespeare's sonnets, with one sonnet per line and words separated by a space.

```
filename = "exampleSonnetsDocuments.txt";
emb = trainWordEmbedding(filename)
Training: 100% Loss: 3.1471   Remaining time: 0 hours 0 minutes.
emb =
  wordEmbedding with properties:

     Dimension: 100
    Vocabulary: ["and"    "the"    "to"    "my"    "of"    "i"    ...    ]
```

Train Word Embedding from File

- View the word embedding in a text scatter plot using tsne.

```
words = emb.Vocabulary;
V = word2vec(emb,words);
XY = tsne(V);
textscatter(XY,words)
```



Train Word Embedding from Documents

- Train a word embedding using the example data sonnetsPreprocessed.txt. This file contains preprocessed versions of Shakespeare's sonnets. The file contains one sonnet per line, with words separated by a space. Extract the text from sonnetsPreprocessed.txt, split the text into documents at newline characters, and then tokenize the documents.

```
filename = "sonnetsPreprocessed.txt";
str = extractFileText(filename);
textData = split(str,newline);
documents = tokenizedDocument(textData);
```

Train Word Embedding from Documents

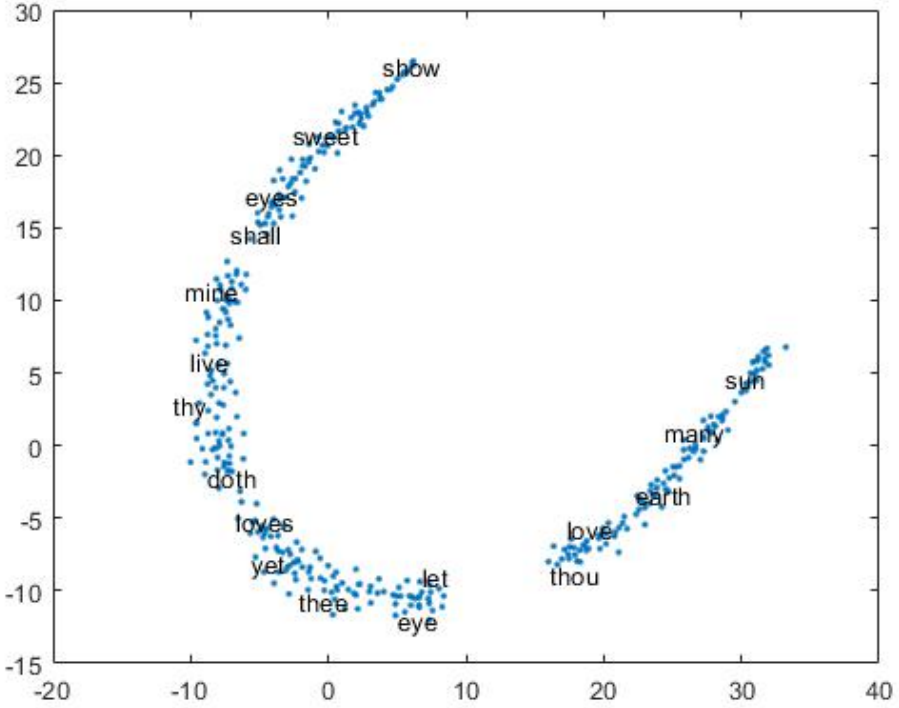
- Train a word embedding using trainWordEmbedding.

```
emb = trainWordEmbedding(documents)
Training: 100% Loss: 0        Remaining time: 0 hours 0 minutes.
emb =
  wordEmbedding with properties:

     Dimension: 100
    Vocabulary: ["thy"    "thou"    "love"    "thee"    "doth"    ...    ]
```

Train Word Embedding from Documents

- Visualize the word embedding in a text scatter plot using tsne.

```
words = emb.Vocabulary;
V = word2vec(emb,words);
XY = tsne(V);
textscatter(XY,words)
```



Specify Word Embedding Options

- Load the example data. The file sonnetsPreprocessed.txt contains preprocessed versions of Shakespeare's sonnets. The file contains one sonnet per line, with words separated by a space. Extract the text from sonnetsPreprocessed.txt, split the text into documents at newline characters, and then tokenize the documents.

```
filename = "sonnetsPreprocessed.txt";
str = extractFileText(filename);
textData = split(str,newline);
documents = tokenizedDocument(textData);
```

Specify Word Embedding Options

- Specify the word embedding dimension to be 50. To reduce the number of words discarded by the model, set 'MinCount' to 3. To train for longer, set the number of epochs to 10.

```
emb = trainWordEmbedding(documents, ...
    'Dimension',50, ...
    'MinCount',3, ...
    'NumEpochs',10)
Training: 100% Loss: 2.7116   Remaining time: 0 hours 0 minutes.
emb =
  wordEmbedding with properties:

     Dimension: 50
    Vocabulary: ["thy"    "thou"    "love"    "thee"    "doth"    ...    ]
```

Specify Word Embedding Options

- View the word embedding in a text scatter plot using tsne.

```
words = emb.Vocabulary;
V = word2vec(emb, words);
XY = tsne(V);
textscatter(XY,words)
```