Deep Learning and Text Mining

Will Stanton

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Return Path Analytics

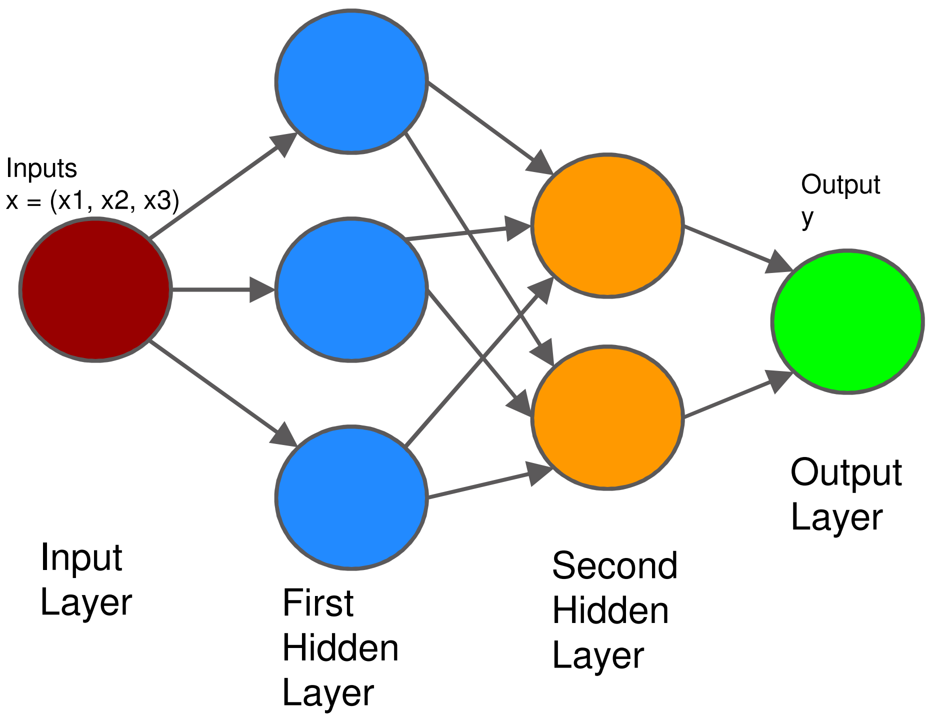
We have a problem

- At Return Path, we process billions of emails a year, from *tons* of senders
- We want to tag and cluster senders
    - Industry verticals (e-commerce, apparel, travel, etc.)
    - Type of customers they sell to (luxury, soccer moms, etc.)
    - Business model (daily deals, flash sales, etc.)
- It's too much to do by hand!

What to do?

- Standard approaches aren't great
    - Bag of words classification model (document-term matrix, LSA, LDA)
        - Have to manually label lots of cases first
        - Difficult with lots of data (especially LDA)
    - Bag of words clustering
        - Can't easily put one company into multiple categories (ie. more general tagging)
        - Needs lots of tuning
- How about deep learning neural networks?
    - Very trendy. Let's try it!

Neural Networks

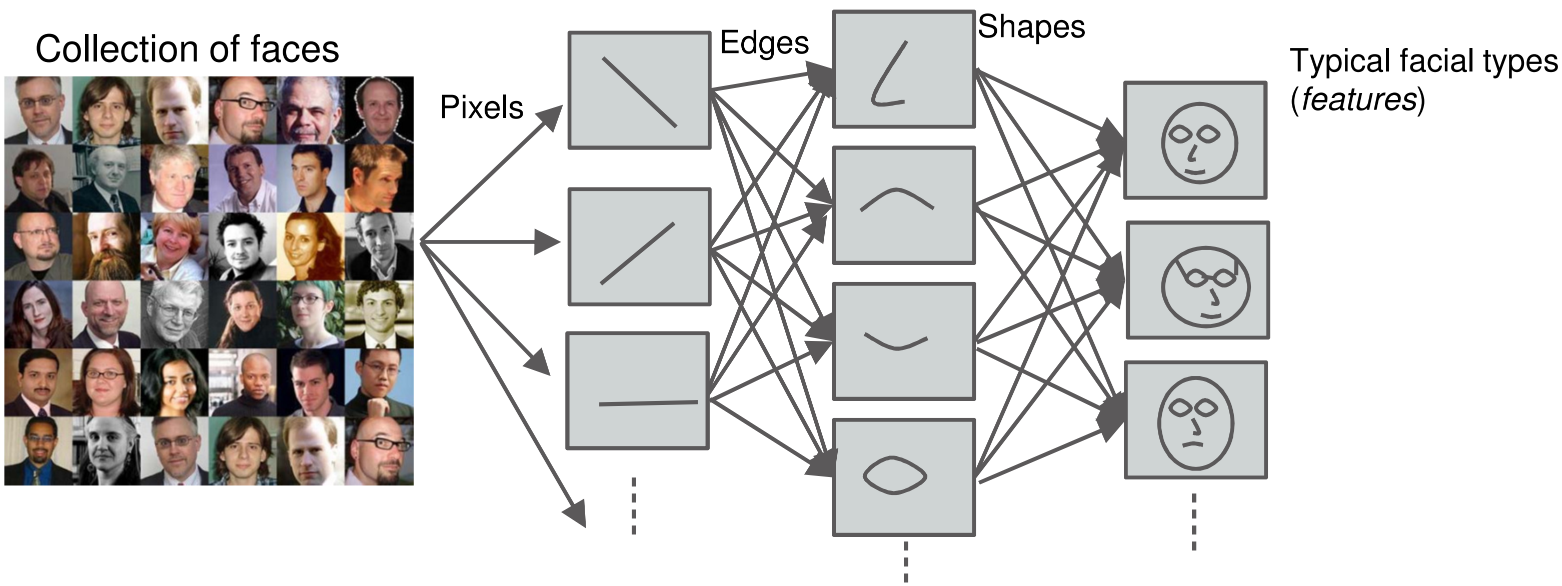


- Machine learning algorithms modeled after the way the human brain works
- Learn patterns and structure by passing **training data** through "**neurons**"
- Useful for classification, regression, feature extraction, etc.

Deep Learning

- Neural networks with *lots* of hidden layers (hundreds)
- State of the art for machine translation, facial recognition, text classification, speech recognition
  - Tasks with real *deep* structure, that humans do automatically but computers struggle with
  - Should be good for company tagging!

Distributed Representations



- Human brain uses distributed representations
- We can use deep learning to do the same thing with words (letters -> words -> phrases -> sentences -> …)

Deep Learning Challenges

- Computationally difficult to train (ie. slow)
  - Each hidden layer means more parameters
  - Each feature means more parameters
- Real human-generated text has a near-infinite number of features and data
  - ie. slow would be a problem
- Solution: use *word2vec*

word2vec

- Published by scientists at Google in 2013
- Python implementation in 2014
    - *gensim* library
- Learns ***distributed vector representations*** of words ("word to vec") using a neural net
    - NOTE for hardcore experts: word2vec does not *strictly* or *necessarily* train a *deep* neural net, but it uses deep learning technology (distributed representations, backpropagation, stochastic gradient descent, etc.) and is based on a series of deep learning papers

What is the output?

- Distributed vector representations of words
  - each word is encoded as a vector of floats
  - vec_{queen}= (0.2, -0.3, .7, 0, … , .3)
  - vec_{woman} = (0.1, -0.2, .6, 0.1, … , .2)
  - length of the vectors = dimension of the word representation
  - **key concept of word2vec**: words with similar vectors have a similar meaning (context)

word2vec Features

- Very fast and scalable
  - Google trained it on 100’s of billions of words
- Uncovers deep latent structure of word relationships
  - Can solve analogies like King::Man as Queen::? or Paris::France as Berlin::?
  - Can solve “one of these things is not like another”
  - Can be used for machine translation or automated sentence completion

How does it work?

- Feed the algorithm (lots of) sentences
  - totally *unsupervised* learning
- word2vec trains a neural net that encodes the *context* of words within sentences
  - “Skip-grams”: what is the probability that the word “queen” appears 1 word after “woman”, 2 words after, etc.

word2vec at Return Path

- At Return Path, we implemented *word2vec* on data from our Consumer Data Stream
  - billions of email subject lines from millions of users
  - fed 30 million unique subject lines (300m words) and sending domains into *word2vec* (using Python)

Lots of subject lines → *word2vec* → word vectors → insights

Grouping companies with *word2vec*

- Find daily deals sites like Groupon

```
[word for (word, score) in model.most_similar('groupon.com', topn = 100) if
  '.com' in word]
['grouponmail.com.au', 'specialicious.com', 'livingsocial.com', 'deem.com',
  'hitthedeals.com', 'grabone-mail-ie.com', 'grabone-mail.com', 'kobonaty.com',
  'deals.com.au', 'coupflip.com', 'ouffer.com', 'wagjag.com']
```

- Find apparel sites like Gap

```
[word for (word, score) in model.most_similar('gap.com', topn = 100) if '.com'
  in word]
['modcloth.com', 'bananarepublic.com', 'shopjustice.com', 'thelimited.com',
  'jcrew.com', 'gymboree.com', 'abercrombie-email.com', 'express.com',
  'hollister-email.com', 'abercrombiekids-email.com', 'thredup.com',
  'neimanmarcusemail.com']
```

More *word2vec* applications

- Find relationships between products
  - `model.most_similar(positive=['iphone', 'galaxy'], negative=['apple']) = ‘samsung’`
  - `ie. iphone::apple as galaxy::?` **`samsung!`**
- Distinguish different companies
  - `model.doesnt_match(['sheraton','westin','aloft','walmart']) = ‘walmart’`
  - `ie. Wal Mart does not match Sheraton, Westin, and Aloft hotels`
- Other possibilities
  - Find different companies with similar marketing copy
  - Automatically construct high-performing subject lines
  - Many more...

Try it yourself

- C implementation exists, but I recommend Python
  - *gensim* library: https://radimrehurek.com/gensim/
  - tutorial:http://radimrehurek.com/gensim/models/word2vec.html
  - webapp to try it out as part of tutorial
  - Pretrained Google News and Freebase models: https://code.google.com/p/word2vec/

Thanks for listening!

- Many thanks to:
  - Data Science Association and Level 3
  - Michael Walker for organizing
- Slides posted on http://will-stanton.com/
- Email me at will@will-stanton.com
- Return Path is hiring! Voted #2 best midsized company to work for in the country http://careers.returnpath.com/