Taste and Tell

An automatic review generator and Restaurant Recommender system

Vasu Sharma Gundeep Arora Peshal Agarwal
Group:27
(Course Instructor: Prof. Harish Karnick)

Indian Institute of Technology, Kanpur

October 30, 2017

Problem Statement

We plan to provide the user the following features:

- A recommender system to provide personalized recommendations
- Review summarizer
- Sentiment analysis and auto-rating from reviews
- Automatic review generation

Recommender system

- Collaborative Deep Filtering approach based on Bayesian Stacked Autoencoder networks
- Vectors drawn from latent Bayesian space are learnt using the user-rating data using EM style algorithm
- Form effective deep feature representation from content and capture the similarity and implicit relationship between groups of items and users

Sentiment Analysis of Reviews

- Paragraph vectors for generating vector embeddings of reviews
- Also experiment with BOW, tf-idf-BoW, BOV, LSTM etc
- Assigning scores to these documents in the range 1 to 5
- Use various classification techniques such as Random Forest, SVC using RBF kernel

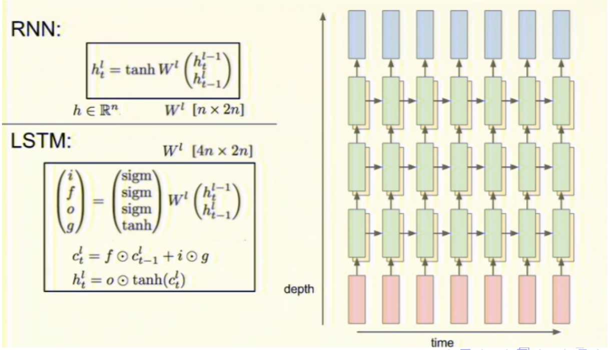
Review Summarisation

Latent Semantic Analysis (LSA)[4]

- Deploys SVD for a matrix where each row represents a frequency weighted sentence vector to extract semantic features of each sentence in a latent space
- LexRank: Graph-based Centrality as Salience in Text Summarization[2]
    - Based on eigenvector centrality of graphical representation of sentences
    - represents sentence as the N(no. of all possible words) dimensional vector with the value of each dimension equal to frequency of word times the idf of word.
- New Methods in Automatic Extracting (Edmundson)[1]
    - Four components from document to convey meaning
    - Gives positive weights to for desired sentences and penalty weights for undesired sentences
- The LexRank algorithm outperforms the other 2 algorithms

Review Generator

- Uses char-rnn model pre-trained on Google News corpus, the goal is to predict the next character in the sequence
- Inputs a user id and score and outputs a sequence of characters till we reach the required length
- We sample from the conditional distribution $P(x_{t+1}|x \leq t)$ to get the next character in a generated string

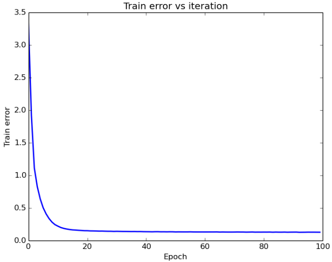


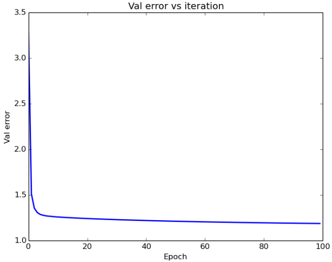
Joint training model of sentiment analyser and review generator

We train a joint model to simultaneously generate reviews and perform sentiment analysis

- The output of review generator becomes input to sentiment analyser
- Euclidean error between predicted and actual score used as error
- Correlation measure used as
- Networks trained separately first
- Both Networks jointly finetuned in an end to end manner

Recommender System





Algorithm	Test set error	Error on augmented dataset
Collaborative Filtering	1.425	1.287
Deep Recommender system	**1.186**	**0.822**

Table: Mean Squared errors for recommender system

Dataset	LSA	Edmundson	LexRank
DUC-2001	0.48	0.42	**0.58**

Table: Rogue-1 Scores [3] for document summarization for DUC dataset

Results: Review Summarization(contd..)

Actual review:"My Cats Are Not Fans of the New Food. My cats have been happily eating Felidae Platinum for more than two years. I just got a new bag and the shape of the food is different. They tried the new food when I first put it in their bowls and now the bowls sit full and the kitties will not touch the food. I've noticed similar reviews related to formula changes in the past. Unfortunately, I now need to find a new food that my cats will eat."

Summary generated:"My cats have been happily eating Felidae Platinum for more than two years.

I've noticed similar reviews related to formula changes in the past.

Unfortunately, I now need to find a new food that my cats will eat.

"

Results: Sentiment Analysis

Feature Representation	Classifier	Accuracy(%)
BoW	Linear SVC	68.2
BoW	Perceptron	69.7
tf-idf weighted BoW	linear SVC	72.5
tf-idf weighted BoW	Perceptron	75.6
BOV	linear SVC	70.2
BOV	Perceptron	72.3
Direct LSTM	N.A.	89.7
Paragraph Vector	Linear SVC	85.5
Paragraph Vector	Perceptron	88.2
Paragraph Vector	**SVM+RBF kernel**	**92.6**

Table: Accuracy Scores for Sentiment Analysis

Results: Jointly trained Sentiment Analysis and Review geenrator

Feature Representation	Classifier	Accuracy(%)
Direct LSTM	N.A.	90.6
Paragraph Vector	Linear SVC	87.4
Paragraph Vector	Perceptron	90.3
Paragraph Vector	**SVM+RBF kernel**	**94.8**

Table: Accuracy Scores for Sentiment Analysis after finetuning

Finetuned(yes/no)	correlation score
No	0.87
Yes	**0.94**

Table: Accuracy Scores for Review generator after finetuning

References I

H. P. Edmundson.
New methods in automatic extracting.
Journal of the ACM (JACM), 1969.

G. Erkan and D. R. Radev.
Lexrank: Graph-based centrality as salience in text summarization, 2004.

C. Y. Lin.
Looking for a few good metrics: Rogue and it's evaluation.
NTCIR, 2004.

J. Steinberger and K. Jezek.
Using latent semantic analysis in text summarization and summary evaluation.
ISIM, 2004.

THANK YOU