GoodToGo : Restaurant Review Summarization System

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Abstract—*Talking about restaurants to dine in, a customer would consider various aspects about the place before choosingto go there such as the food, ambience and service. Deciding onwhat and where to eat is a task when we wish to go out due to a wide range of choices in both, food and place. Also choosing the right dish at the right time seems to be a very difficult. Therefore, we propose a system which will summarize restaurants using reviews and help customers choose a restaurant and also help in deciding what order to place.*

Keywords—dine, food, ambience, service, customers, restaurant, summarize

1. INTRODUCTION

In today's times, considering that people enjoy dining in various restaurants we attempt to make their experience more personalized by helping them to choose a place. Internet is rife with comments and feedback about food satisfaction backed by reviews from food enthusiasts that have visited substantiate number of restaurants. This cornucopia of information can be used to provide customers get valuable knowledge about a particular food dish across various restaurants.

Nowadays, which such an increase in the number and variety of food locations opening up in cities, it has become challenging to choose the right place. We all tend to ask for food suggestions from people we know before visiting the place. There are also many food bloggers and food enthusiasts who often mention their detailed experience of visiting the restaurant in the reviews. We aim to make use of this information and help the user get more detailed insight about the restaurant and make an informed decision.

To make the best use of this helpful information we have used neural networks to process and analyse the reviews. In doing so it is essential for the model to memorize the entire sentence and capture the context of the words used. Hence, we used Recurrent Neural Networks (RNNs) , especially Bidirectional Long Short Term Memory (Bi-LSTM) model to understand and recognize the desired entity from the text. Further, we used grammar rules to extract the relevant entityphrases and proceed with sentiment analysis of the same. Consequently, it helped us to provide advanced summarization of the food dishes.

2. LITERATURE REVIEW

S.Prakhash, A.Nazick, R. Panchendrarajan, M.Brunthavan, S.Ranathunga, A.Pemasiri [1] present two techniques for food name categorization in restaurant reviews using document (text) similarity measurements. The improved Single Pass Partitioning method showed best results. In the enhanced SPPM approach categorization is done considering the individual words in the food names.

Ditdit Nugeraha Utama, Luqman Isyraqi Lazuardi, Hersy Ayu Qadrya, Bella Marisela Caroline, Tris Renanda, AtthiyaPrima Sari [2] proposed an intelligent restaurant recommendation application (WorthEat) by using methods fuzzy-logic and bubble sort. The method fuzzy logic is used to parameterize three selected parameters; interest, location, and rating. And, the bubble-sort is a method to optimize the recommendation based on full-factorial concept. This was implemented for five types of restaurants in Indonesia.

Tossawat Mokdara, Priyakorn Pusawiro and Jaturon Harnsomburana [3] propose a temporal model of recommendation system using deep neural network for Thai food in order to help consumers to make a decision of selecting dish based on individual consumer behaviors, preferences, and eating history. The proposed model extracts interested ingredients from the set of recipes of user's favoritedishes that is given before using the system. The system will recommend food that is customized to the user profile and eating history which makes decision making easier. It could help reducing time to choose the next dish and also satisfy all consumers.

R.M. Gomathi, P.Ajitha, G. Hari Satya, Krishna and I. Harsha Pranay [4] propose a machine learning system for restaurant recommendation based on rating and amenities. It also shows a comparison of various sentimental score measures such as Natural Language Processing, Probabilistic Neural Network, Back Propagation Neural Network, Support Vector Machine and Linear Discriminate Analysis. NLP > PNN > BPN > SVM > LDA tested on data from tripadvisor.com

3. METHODOLOGY

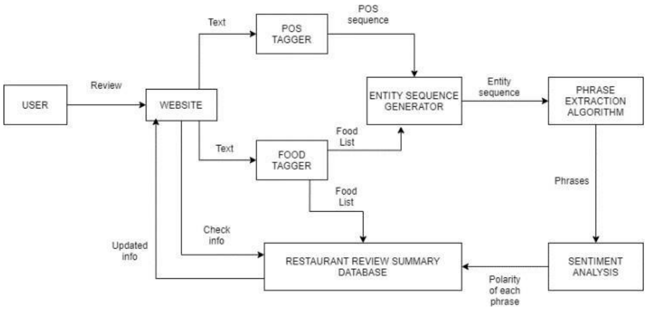


Fig 1. Data flow diagram

The complete methodology can be divided into followingmodules :

- Data collection and pre-processing
- Entity tagging
- Phrase extraction
- Sentiment analysis
- Top dishes summarization

3.1 Data collection and pre-processing

Reviews and menu of restaurants were the data required.Reviews were collected from TripAdvisor using TripAdvisor api. Menu (name of food dishes) were scraped from Zomato. For this, we selected 11 Indian restaurants of varied types andcuisines so as to generalize the dataset to different type of food names and sentence constructs. The type of restaurants included are Italian, Punjabi (North Indian), South Indian, Maharashtrian, fast food corners and cafes. The restaurants were selected by manually inspecting their reviews based on the length of review, whether there were more food describing reviews or not and having equal mix of positive and negative reviews. This data was stored in Excel files with headers as review no. , Sentence no., Word, and POS tag where each word of the review was a row in the file. (Fig 2)

	A	B	C	D	E	F
1		review no	restaurant	sentence no	words	algo_tag
2	278	1	1441 Pizzeria	10	Make	O
3	279	1	1441 Pizzeria	10	your	O
4	280	1	1441 Pizzeria	10	own	O
5	281	1	1441 Pizzeria	10	gourmet	E
6	282	1	1441 Pizzeria	10	pizza	E
7	283	1	1441 Pizzeria	10	(	O
8	284	1	1441 Pizzeria	10	toppings	E
9	285	1	1441 Pizzeria	10	chicken	E
10	286	1	1441 Pizzeria	10	sausages	E
11	287	1	1441 Pizzeria	10	,	O
12	288	1	1441 Pizzeria	10	meat	E
13	289	1	1441 Pizzeria	10	balls	E
14	290	1	1441 Pizzeria	10	,	O
15	291	1	1441 Pizzeria	10	pepperoni	E
16	292	1	1441 Pizzeria	10	)	O

Fig 2. Food entity labelled dataset

3.2 Entity Tagging

The entity in our case were the food dishes. The aim in this module is to tag food dishes in the review sentences. First a rule based approach was used to create a labelled dataset enough to train a ML model to tag entities.

Problem faced : Some of the food dish names contained words which were more general and could be used out of food context . Eg. In "Hot chocolate brownie", the word hot can bein sentence in such a way that it may or may not be a part fooddish name. To tackle this problem, a list a such words were created (names as remove_list) and an algorithm was used to get rid of these unnecessary wrong tagging. This was based onthe fact that such word cannot be a dish name on their own (eg. Hot cannot be a dish name. It is only tagged as entity with it comes along with other food names)

Here, the above the reviews dataset (each word on a row) was imported and each word was checked against the food dishes from the food dishes dataset scraped from Zomato. The matching was were tagged as entity E. This was used as dataset to train a LSTM model to tag entities and after training, this model is used for tagging entities.

Final dataset consists of reviews which are stored word by word on each row. POS tags and entity are the properties associated with each word. Also a final tag column was addedwherein the entity column was copied as it is and the non- entity(non-food dishes) words were filled with their POS tags as in Fig3.

```
['I', 'chose', 'the', 'make', 'your', 'own', 'pizza', 'with', 'unlimited', 'toppings', '.']
['O', 'O', 'O', 'O', 'O', 'O', 'E', 'O', 'O', 'E', 'O']
['PRP', 'VBD', 'DT', 'VB', 'PRP$', 'JJ', 'NN', 'IN', 'JJ', 'NNS', '.']

['PRP', 'VBD', 'DT', 'VB', 'PRP$', 'JJ', 'E', 'IN', 'JJ', 'E', '.']
```

Fig 3. Entity and POS tag combined dataset

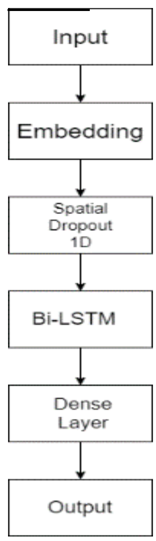
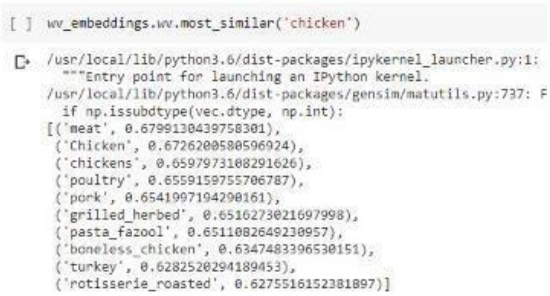


Fig 4. Deep Learning architecture for Food EntityTagging

Word2Vec is a method to construct such an embedding. Google has published a pre-trained word2vec model. It is trained on part of Google News dataset (about 100 billion words). The model contains 300-dimensional vectors for 3 million words and phrases. We performed transfer learning by using these pretrained word vectors to reinforce the learning process of our entity tagging task. This helped accuracy of entity tagging model since it provided knowledge about the general context of words which wouldotherwise take lot of data and resources to learn their meaning from scratch.



```
[ ] wv_embeddings.wv.most_similar('chicken')

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1:
  """Entry point for launching an IPython kernel.
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: F
  if np.issubdtype(vec.dtype, np.int):
[('meat', 0.6799130439758301),
 ('Chicken', 0.6726200580596924),
 ('chickens', 0.6597973108291626),
 ('poultry', 0.6559159755706787),
 ('pork', 0.6541997194290161),
 ('grilled_herbed', 0.6516273021697998),
 ('pasta_fazool', 0.6511082649230957),
 ('boneless_chicken', 0.6347483396530151),
 ('turkey', 0.6282520294189453),
 ('rotisserie_roasted', 0.6275516152381897)]
```

Fig 5. Word Embedding Example

In the example in Fig 5. above, the pretrained word vectors contained information that convey words like chicken, meat, pork, poultry are similar words that relate to each other than most other words. Further, fine tuning the learning model bytraining on our own dataset helped to make this category of food more distinct from others. Dropout layer is used to solve the problem of overfitting.

A RNN using LSTM units is trained in a supervised fashion, on a set of training sequences, using an optimization algorithm, Adam, combined with backpropagation through time to compute the gradients needed during the optimization process, in order to change each weight of the LSTM network with an objective to minimise loss, sparse categorical crossentropy. BiLSTMs effectively increase the amount of information available to the network, improving the context available to the algorithm (e.g. knowing what words immediately follow and precede a word in a sentence).

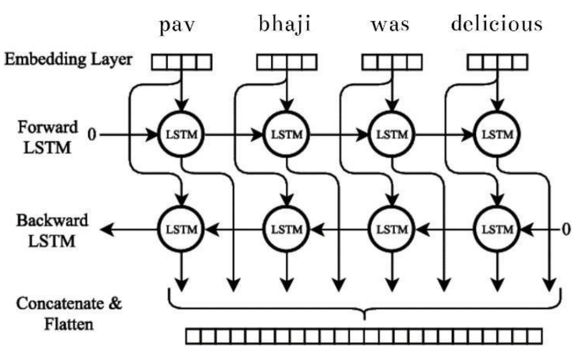


Fig 6. Bi-LSTM model representation

The output of BiLSTM is fed to DNN layer which is usedfor classification task. Softmax activation function is used for classification of entities.

The training dataset contains 5737 reviews and it is tested on 1435 reviews. The sparse categorical accuracy optimised by adam is 99.96% for training set and 99.79% for test set asshown in the Fig 7.

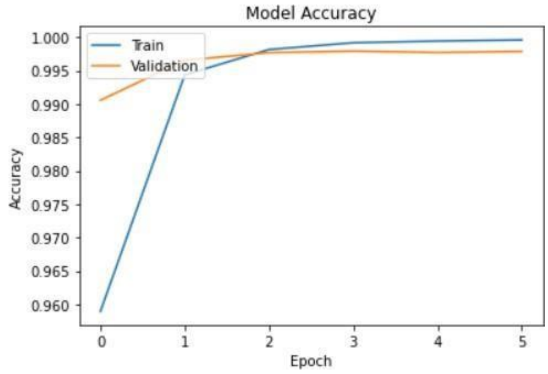


Fig 7. Accuracy of entity tagging model

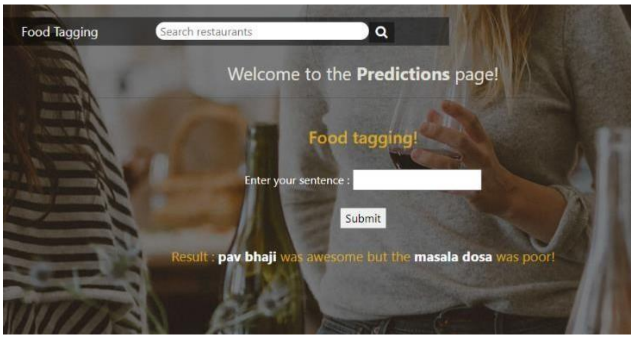


Fig 8. Food entity tagger page

3.3 Phrase Extraction

The aim of this module is to extract food describing phrases from each sentence.

Eg. Input ->This place has the best garlic

bread.Output -->best garlic bread

Grammatical rules - English language has a blur general sense of sentence construct. Generally a phrase which describes something has a few commonly occurring pattern. The most common of it being :

<u>NVA</u> = "PHRASE:{(<JJ|JJR|JJS|NN|NNS|NNP|NNPS>?<E>+<CC>)?<JJ|JJR|JJS|NN|NNS|NNP|NNPS>?<E>+<VB|VBP|VBN|VBD><RB>?<JJ|JJR|JJS|NN|NNS|NNP|NNPS>+}"

<u>AN</u> = "PHRASE:{<RB>?<JJ|JJR|JJS><E>+}"

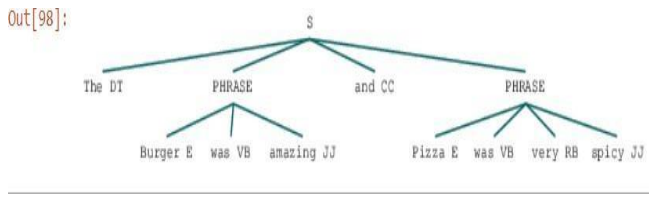


Fig 9. Tree visualization

The adjective phrase and noun phrase which is associatedwith our entity(food) is extracted. The system uses this to parse out phrases from sentences. In this case entity is the name of any food dish and the adjective/noun part is the description of the dish. Every sentence is represented using anarray of tags (entity and POS). Nltk provides a matcher which matches our given sequence with the set of rules we provide to the matcher. So , we use the above mentioned rules (1) and(2) in this matcher to extract phrases. The function then spits out the matched phrases from our sentence. The parsed out phrases are then stored grouped by their restaurant as shownin Fig 10.

Sr no.	Review phrase	Polarity
1	pizza was delicious	1.0
2	Keema pav was delicious	1.0
3	cake was too delicious	1.0
4	food was very good	0.91
5	Pizzas were also great	0.8
6	Oreo shake was good	0.7
7	shakes and parathas are really good	0.7
8	Parathas and Shakes are good	0.7
9	parathas and beer lassi remain fair	0.7
10	food was good	0.7
11	Shakes are ok	0.5
12	Paratha was worth	0.3
13	nachos were crisp	0.25
14	Amritsari kulcha was so crisp	0.25
15	veggie delight and barbeque chicken pizzas are delicious	0.2
16	Food was decent	0.166666667
17	Chicken shawarma was good	0.05
18	Nachos were piquant	0.0
19	food was average	-0.15
20	Masala paratha was little bit spicy	-0.1875
21	Waiter was rude	-0.3
22	Chicken and other toppings were few	-0.308333333
23	brownie seemed stale	-0.5

Fig 10. Extracted phrases with sentiment

3.4 Sentiment Analysis

The system uses textblob for sentiment analysis. The sentiment function of textblob returns the polarity of the phrase. Based on this we get polarity for each phrase and hence the system recognizes it as a positive phrase or negativephrase.

The polarity of extracted phrases is shown on the website as in Fig 9.

3.5 Top dishes summarization

The food item in each phrase is then identified again and then the phrases are grouped according to food dish. A combined aggregate polarity score for the dish is calculated and hence the food item is classified into what's best to orderand what's not. (Refer Fig 10.)

Here is our summary for *Elco* Restaurant!

Top Favorite dishes!

Sr no.	Dish Name	Polarity
1	chole bhature	1.0
2	pao bhaji	1.0
3	pani puris	0.8
4	delhi style chaats	0.7
5	sev puri	0.7
6	aloo tikki chole	0.6
7	snacks	0.2875
8	choices	0.25
9	bhel	0.166666667
10	boondi	0.13636363599999998
11	food	0.125
12	bhaji	0.0
13	tawa pulao	-0.15
14	pani puri	-0.375
15	strawberry falooda	-0.6

Fig 11. Top food dishes

4. CONCLUSIONS

The system is able to identify food dishes from lengthy reviews with good accuracy. Phrase extraction from reviewsusing grammatical rules proves effective when the structure of sentence is of the form Entity-verb-adj/noun. Users can get aglance at popular food item phrases at any restaurant and also get a summarized sentiment of the top dishes. All these features are deployed on the website which gives users easy access to these services.

FUTURE SCOPE

The model is designed to extract phrases only relevant to food entities. This methodology can be extended to extract and summarize ambience and service for the restaurant. Custom model for sentiment analysis and POS tagging that is trained on food reviews dataset will give better results. Larger dataset can be taken to generalize summarization on a broader range of reviews and improve the accuracy of the overall model.

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