NLP-BASED FOOD SUGGESTIONS SYSTEM – SMART HOMES

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ABSTRACT

With advanced AI, every industry is growing at rocket speed, while the smart home industry has not reached the next-generation level. A home can only be called a real smart home, when it is completely smart and understand what the residents want, and provide service in a timely manner. The residents should live in the house as if they are leaving in a motel while the house itself takes care of itself and give extra benefits to residents like providing food suggestions to the residents for everyday meals based on their taste, culture, weather, type of their food diet, their interest to try new recipes etc. Our system is an NLP Bert model-based similarity prediction model. The system ranks the recipes based on the similarity of the words and context. Recipes have similar ingredients and procedures are considered similar recipes. Overall, the system creates the top K number of recipes based n the number of days' history of eating habits and removes products that are similar to the recent m number of days to make sure the suggestions are not quite repetitive (here m<<<<n).

KEYWORDS

Food Suggestion System, Bert, Item Similarity

1. INTRODUCTION

Food is any substance consumed by an organism for nutritional support. In earlier days, food used be simple fruits or raw meat. But with time people started appreciating cooked food with different methods and ingredient combinations. While many foods can be eaten raw, many also undergo some form of preparation for reasons of safety, palatability, texture, or flavor. At the simplest level this may involve cutting, trimming, or adding other foods or ingredients, such as spices. It may also involve mixing, heating or cooling, pressure cooking, fermentation, or combination with other food. Some preparation is done to enhance the taste or aesthetic appeal; other preparation may help to preserve the food; others may be involved in cultural identity. But based on different people's tastes, they try different types of foods made in cooking methods: a vast range of methods, tools, and combinations of ingredients to improve the flavor or digestibility of food. Some people love coriander, while others hate it. You might like olives, but maybe your dad thinks they're disgusting. There are different theories on why people like what they like such as genetics etc. People's tastes are also affected by the culture of the people they came from. People also connect to their cultural or ethnic groups through food patterns. Food is often used as a means of retaining their cultural identity. Culturally speaking, Asian food tends to use opposing flavours in dishes,like mixing salty with sweet or sweet and sour together while a Western dish often focuses on a particular type of flavour like savoury or sweet. Based on their native place, their current location along with the food experiences they had people tend to appreciate different types of foods.

But understanding who can like what food is an interesting problem, especially in smart homes. As a part of our smart home project, we experimented on a food suggestions system to recommend a food menu to the residents based on their interests. Now a days, along with friends' suggested movies, everyone is following a suggestions list on internment websites like Netflix to consider any new movies or other entertainment. As an extension to it, Recommendation systems will rule the food recommendations system in the future. people appreciate and try different movies and foods suggested by their friends and well-wishers who know their tastes and have exposure to other similar foods. These applications can be quite useful in restaurants business, groceries business, and online food ordering apps like Doordash, Uber eats, etc.

While there are several ways to implement this problem such as co-occurrence matrix, FP-growth etc. But we choose to go with NLP based item similarity model as it gave decent results provided the condition that we have very less user to user data as our smart home systems are in the initial stages of data collection. But we were able to develop this model using open source recipe data set(item-to-item data set).

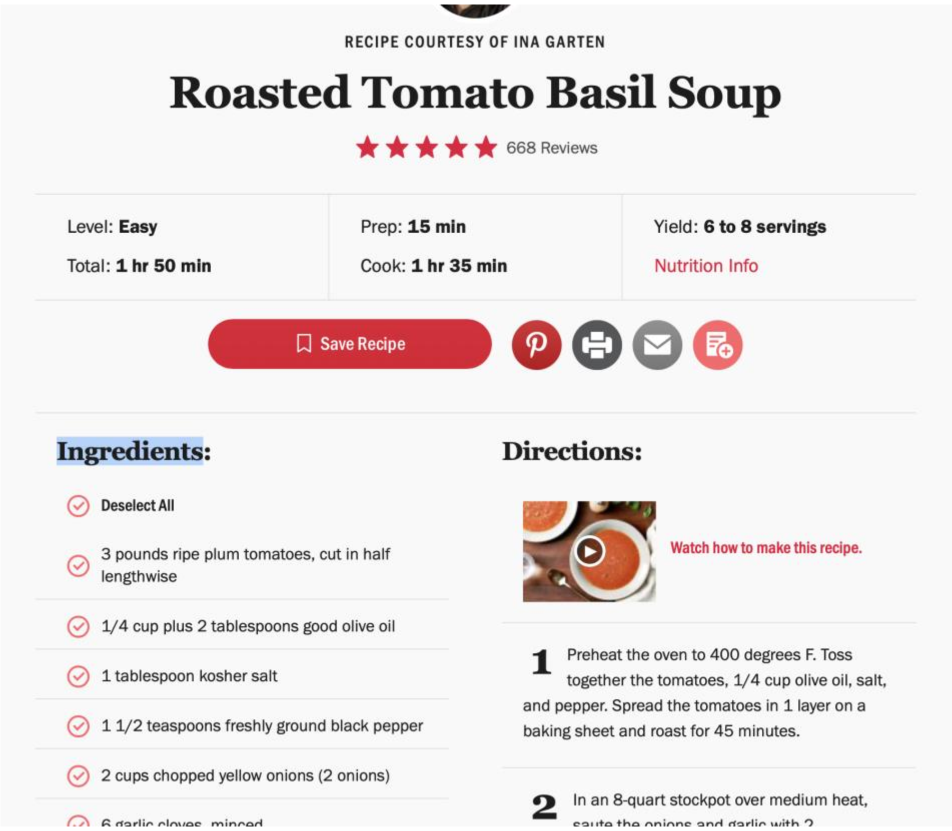
2. RESEARCH IN INDUSTRY

While Bert NLP based similarly prediction systems became quite famous in recent days, food prediction systems are still growing. A team at IRJET, India has developed a Food recommendation system that makes suggestions based on Food profiling, User profiling, and the last feedback submitted by the users. A team at SDMCET Dharwad, India has developed food recommendations based on deep learning. we can also see a lot of research in the healthy food domain. Different institutes like the Graz University of Technology, Graz, Austria developed recommendations in the healthy food domain. Our paper is naïve as it's developed based on NLP. And this system is simple as it's based on Bert rather than a separate deep learning model.

3. MODEL BUILDING

As mentioned before, our model is based on text and NLP-based similarity systems. Some of the important factors of a recipe and its taste are the ingredients used, in which sequence they are used. NLP models especially Bert that concentrate on the similarity of words and the similarity of the sentences (on other terms sequence) can effectively capture them. To explain this further, a person who likes raw tomatoes most likely appreciates salsa and tomato soup. To give a more complicated example, an Indian who appreciates hot chicken curry with rice most likely appreciates panda express Black Pepper Chicken with fried rice. A north India that appreciate chapatis (wheat flat bread) with Alu curry is mostly likely to appreciate Mexican corn veg alu tacos. The similar the ingredients and the cooking process, the more the user can like that recipe more.

Infact, when a human (friends or known people) suggested a recipe to others, they also follow same thinking process. If a person likes rice, spices and hot food, they people eventually suggest Indian food. This is a best example which explains the importance of ingrediants and it's combinations. In addition, some other factors like how much it's cooked (well cooked, half cooked, raw), whether it consists of some ingredients the user cannot eat also influence their final food interests. For example, someone whose very sensitive to spices or hotness, might not appreciate Nashville Hot chicken though he like chicken in general.



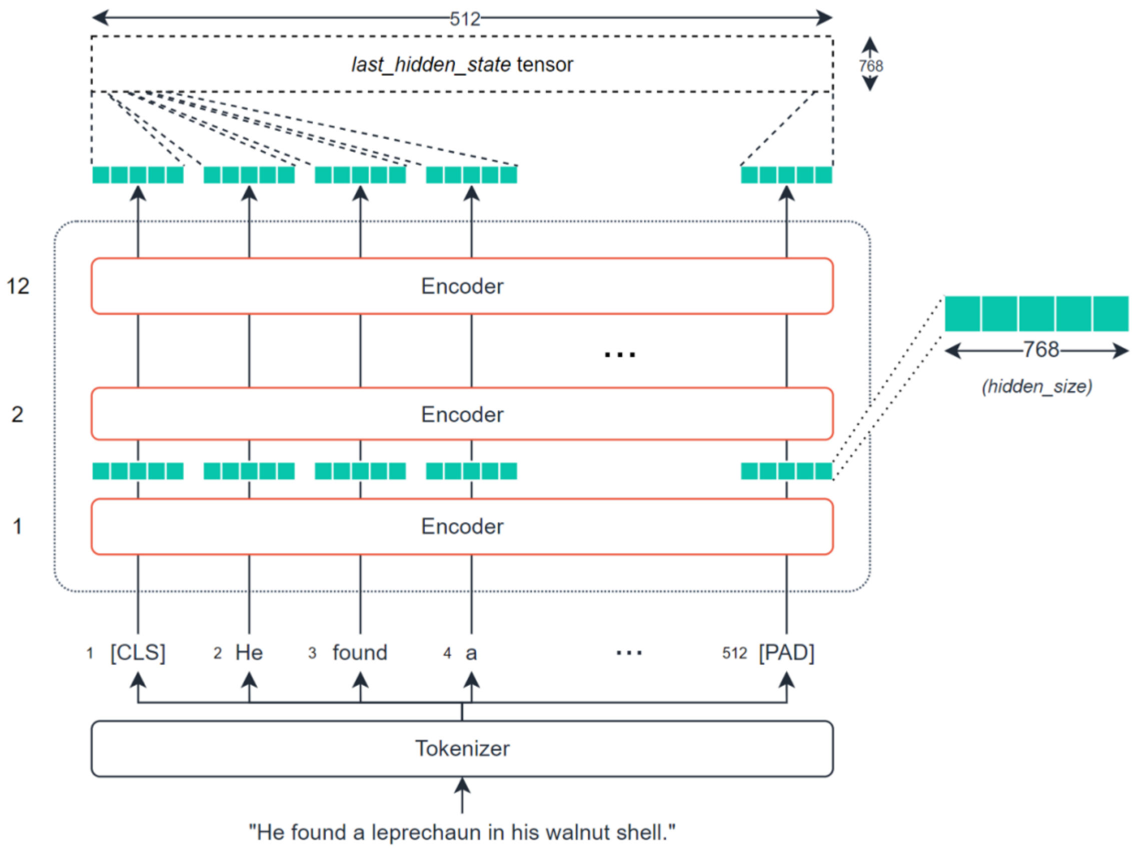
3.1. BERT For Measuring Text Similarity:

Why BERT Helps:

BERT, as we already mentioned — is the MVP of NLP. And a big part of this is down to BERTs ability to embed the meaning of words into densely packed vectors.

We call them dense vectors because every value within the vector has a value and has a reason for being that value — this is in contrast to sparse vectors, such as one-hot encoded vectors where the majority of values are 0.

BERT is great at creating these dense vectors, and each encoder layer (there are several) outputs a set of dense vectors.



BERT base network — with the hidden layer representations highlighted in green.

For BERT base, this will be a vector containing 768. Those 768 values contain our numerical representation of a single token — which we can use as contextual word embeddings.

Because there is one of these vectors for representing each token (output by each encoder), we are actually looking at a tensor of size 768 by the number of tokens.

We can take these tensors — and transform them to create semantic representations of the input sequence. We can then take our similarity metrics and calculate the respective similarity between different sequences.

The simplest and most commonly extracted tensor is the last_hidden_statetensor — which is conveniently output by the BERT model.

Of course, this is a pretty large tensor — at 512x768 — and we want a vector to apply our similarity measures to it.

To do this, we need to convert our last_hidden_states tensor to a vector of 768 dimensions.

Creating The Vector

For us to convert our last_hidden_states tensor into our vector — we use a mean pooling operation.

Each of those 512 tokens has a respective 768 values. This pooling operation will take the mean of all token embeddings and compress them into a single 768 vector space — creating a ‘sentence vector’.

At the same time, we can’t just take the mean activation as is. We need to consider null padding tokens (which we should not include).

Easy — Sentence-Transformers

The easiest approach for us to implement everything we just covered is through the sentence-transformers library — which wraps most of this process into a few lines of code.

First, we install sentence-transformers using pip install sentence-transformers. This library uses HuggingFace's transformers behind the scenes — so we can actually find sentence-transformers models here. We'll be making use of the bert-base-nli-mean-tokens model.

3.2. Data set introduction

As mentioned above, as our smart home systems are in the initial stages of data gathering, we have utilized open-source recipes information (item description) and developed a recipe to recipe similarity recommendation(item to item similarity prediction). Which can be a perfect start for our service. We have utilized RecipeNLG dataset: A Cooking Recipes Dataset for Semi-Structured Text Generation. Some description about the dataset.

RecipeNLG_dataset.csv (2.29 GB)

Detail Compact Column 7 of 7 colum

#	title	ingredients	directions	link	source	NER
0 2.23m	1312871 unique values	2226362 unique values	2211644 unique values	2231142 unique values	Gathered 74% Recipes1M 26%	2133496 unique values
0	No-Bake Nut Cookies	["1 c. firmly packed brown sugar", "1/2 c. evaporated milk", "1/2 tsp. vanilla", "1/2 c. broken nuts...	["In a heavy 2-quart saucepan, mix brown sugar, nuts, evaporated milk and butter or margarine.", "St...	www.cookbooks.com/Recipe-Details.aspx?id=44874	Gathered	["brown sugar", "milk", "vanilla", "nuts", "butter", "bite size shredded rice biscuits"]
1	Jewell Ball'S Chicken	["1 small jar chipped beef, cut up", "4 boned chicken breasts", "1 can cream of mushroom soup", "1 c...	["Place chipped beef on bottom of baking dish.", "Place chicken on top of beef.", "Mix soup and crea...	www.cookbooks.com/Recipe-Details.aspx?id=699419	Gathered	["beef", "chicken breasts", "cream of mushroom soup", "sour cream"]
2	Creamy Corn	["2 (16 oz.) pkg. frozen corn", "1 (8 oz.) pkg. cream cheese, cubed", "1/3 c. butter, cubed", "1/2 t...	["In a slow cooker, combine all ingredients. Cover and cook on low for 4 hours or until heated throu...	www.cookbooks.com/Recipe-Details.aspx?id=10570	Gathered	["frozen corn", "cream cheese", "butter", "garlic powder", "salt", "pepper"]
3	Chicken Funny	["1 large whole chicken", "2 (10 1/2 oz.) cans chicken gravy", "1 (10 1/2 oz.) can cream of mushroom...	["Boil and debone chicken.", "Put bite size pieces in average size square casserole dish.", "Pour gr...	www.cookbooks.com/Recipe-Details.aspx?id=897570	Gathered	["chicken", "chicken gravy", "cream of mushroom soup", "shredded cheese"]
4	Reeses Cups(Candy)	["1 c. peanut butter", "3/4 c. graham cracker crumbs", "1 c. melted butter", "1 lb. (3 1/2 c.) powde...	["Combine first four ingredients and press in 13 x 9-inch ungreased pan.", "Melt chocolate chips and...	www.cookbooks.com/Recipe-Details.aspx?id=659239	Gathered	["peanut butter", "graham cracker crumbs", "butter", "powdered sugar", "chocolate chips"]

RecipeNLG_dataset.csv (2.29 GB)

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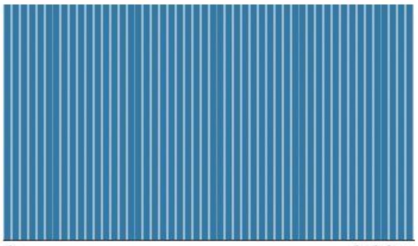

Valid	2.23m	100%
Mismatched	0	0%
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Mean	1.12m	
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A link

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unique values

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Missing	0	0%
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Most Common	www.c...	0%

A source

Gathered	74%
Recipes1M	26%

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Missing	0	0%
Unique	2	
Most Common	Gathered	74%

A NER

2133496
unique values

Valid	2.23m	100%
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Missing	0	0%

3.1. Item To Item Similarity System Development:

Based on the NLP Bert embeddings which consist of word similarity(covers ingredients) and as well as sentence similarity(which covers the procedure easily), I achieved the similarity measurable data from text data. In this stage, I just utilized cosine similarity to find similar embeddings and further similar recipes. As mentioned before this methodology is completely an item-to-item similarity problem. A model similar to the next prediction transaction models (in marketing) should be added to repeat the recipes as per the user interest. In addition, I don't want to keep the suggested item very diverse. For that, we implemented a logic to avoid similar items to last week's menu.

Steps:

1] Predict similar items to all the menu of the last 1 year.

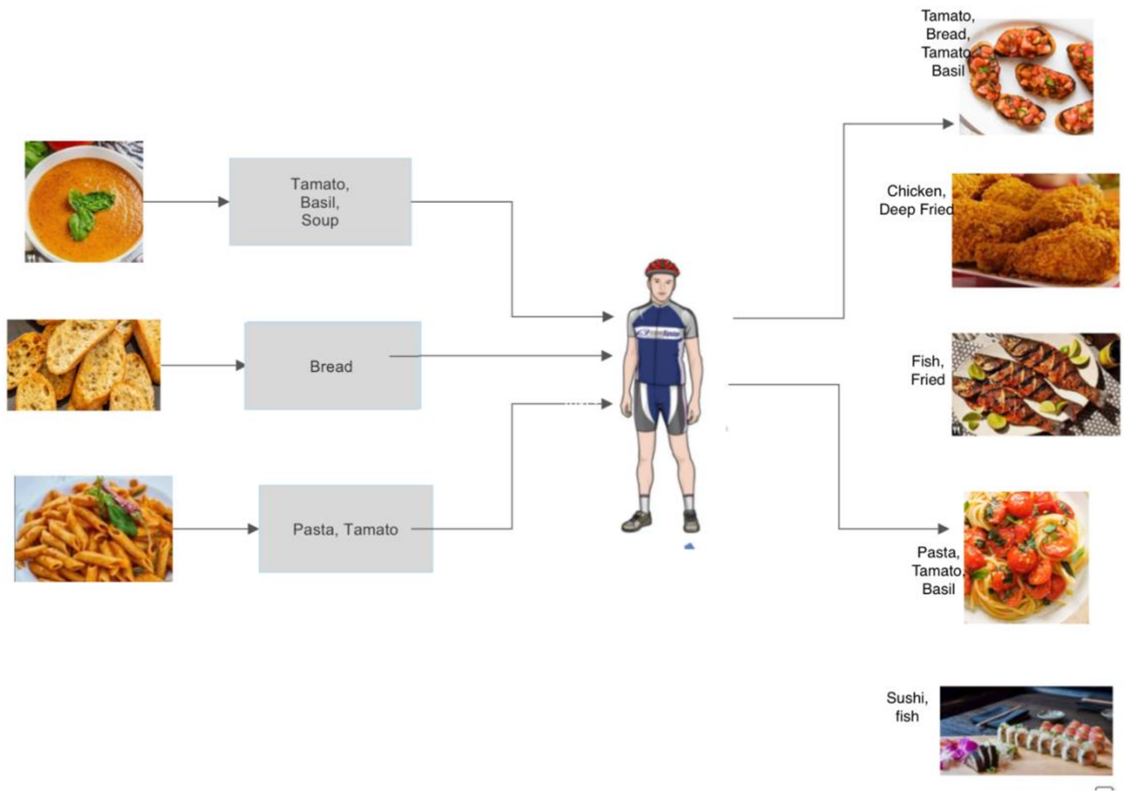
2] Aggregate the similarities we got for every product's top 10 items.

3] The top M consider them as final year production list.

4] Find the similarity of the final year production list items with every item in the last 2 weeks' menu.

5] Suggest the least similar one. (The items with less similarity score)

This methodology on one side covers the user-interested ingredients and skips the recent recipes.



4. RESULTS

Bert word embeddings

```
Item_bert_Based_Embeddings

array([[-0.5876694 ,  0.9624591 , -0.6597185 , ...,  0.20095427,
         0.88454515,  0.17805354],
       [-0.68774587,  1.2468425 , -0.21277218, ...,  0.03516852,
         0.60958594,  0.6736125 ],
       [-0.48815408,  0.69607776, -0.587878  , ...,  0.4016425 ,
         0.90484554,  0.088472  ],
       ...,
       [-0.5892445 ,  0.55875134, -0.31674802, ...,  0.7757392 ,
         0.33361197, -0.38579077],
       [-0.5535985 ,  1.0312567 , -0.1764647 , ...,  1.1586254 ,
         0.8058038 ,  0.40962666],
       [-0.9345914 ,  1.3805144 , -0.554982  , ...,  0.5943564 ,
         0.61359185,  0.3393082 ]], dtype=float32)
```

An example showing similar items.

```
46796    ["1 can cream of chicken soup", "1 (16 oz.) ca...
dtype: object
>>> sentences[index].values
array(['["2 (16 oz.) pkg. frozen corn", "1 (8 oz.) pkg. cream cheese, cubed", "1/3 c. butter, cubed", "1/2 tsp. garlic powder", "1/2 tsp. salt
", "1/4 tsp. pepper"] Creamy Corn ["In a slow cooker, combine all ingredients. Cover and cook on low for 4 hours or until heated through and c
heese is melted. Stir well before serving. Yields 6 servings."] Gathered ["frozen corn", "cream cheese", "butter", "garlic powder", "salt", "p
epper"]',
       '["1 small jar chipped beef, cut up", "4 boned chicken breasts", "1 can cream of mushroom soup", "1 carton sour cream"] Jewell Ball\'S
Chicken ["Place chipped beef on bottom of baking dish.", "Place chicken on top of beef.", "Mix soup and cream together; pour over chicken. Bak
e, uncovered, at 275\\u00b0 for 3 hours."] Gathered ["beef", "chicken breasts", "cream of mushroom soup", "sour cream"]',
       '["1 large whole chicken", "2 (10 1/2 oz.) cans chicken gravy", "1 (10 1/2 oz.) can cream of mushroom soup", "1 (6 oz.) box Stove Top s
tuffing", "4 oz. shredded cheese"] Chicken Funny ["Boil and debone chicken.", "Put bite size pieces in average size square casserole dish.", "
Pour gravy and cream of mushroom soup over chicken; level.", "Make stuffing according to instructions on box (do not make too moist).", "Put s
tuffing on top of chicken and gravy; level.", "Sprinkle shredded cheese on top and bake at 350\\u00b0 for approximately 20 minutes or until go
lden and bubbly."] Gathered ["chicken", "chicken gravy", "cream of mushroom soup", "shredded cheese"]',
       '["4 chicken breasts, boned", "1 pkg. chipped beef", "1/2 pt. sour cream", "1 can cream of mushroom soup", "6 strips bacon, cooked cris
p"] Creamy Chicken ["Place chicken breasts in Pam-sprayed pan.", "Put small pieces of chipped beef over chicken.", "Mix sour cream and mushroo
m soup and pour over chicken.", "Crumble bacon and sprinkle on top.", "Bake at 300\\u00b0 for 2 hours, uncovered."] Gathered ["chicken breasts
", "chipped beef", "sour cream", "cream of mushroom soup", "bacon"]',
       '["8 chicken breasts, boned and skinned", "1 pkg. dried beef", "1 can cream of mushroom soup", "1/2 pt. sour cream"] Chicken Woodruff [
"Line baking dish with beef.", "Wrap each breast with slice of bacon and place on top of beef.", "Mix soup and sour cream and pour over chicke
n.", "Bake uncovered at 225\\u00b0 for 3 hours."] Gathered ["chicken breasts", "dried beef", "cream of mushroom soup", "sour cream"]',
       '["4 whole boned chicken breasts, cut in half", "1 jar Armour dried beef", "1 can cream of mushroom soup", "1 c. sour cream", "bacon"]
Chicken Surprise ["Wrap each piece of chicken in a piece of bacon.", "Put each piece of chicken on 2 slices of dried beef in a casserole dish.
 Use one so the chicken fits snug in the dish.", "Mix 1 can cream of mushroom soup and 1 cup sour cream together and spread over chicken.", "B
ake at 250 degrees for 5 hours uncovered."] Gathered ["chicken breasts", "Armour dried beef", "cream of mushroom soup", "sour cream", "bacon"]
',
       '["1 (about 2 1/2 oz.) jar sliced beef, rinse and drain", "4 whole chicken breasts, split, skinned and deboned", "2 cans cream of mushr
oom soup", "1 c. sour cream", "6 slices bacon, cut in half"] Special Chicken Breast ["In shallow baking pan (13 x 9 x 2-inch), arrange single
layer of beef.", "Top with chicken.", "Blend soup and sour cream.", "Pour over all. Top with bacon. Cover and bake 3 hours at 250\\u00b0. Then
 bake uncovered for 1 additional hour."] Gathered ["beef", "chicken breasts", "cream of mushroom soup", "sour cream", "bacon"]',
       '["boned, uncooked chicken breasts", "slices of bacon", "1 jar dried beef", "1 can cream of chicken soup", "sour cream", "paprika"] Chi
cken Supreme ["Line pan with dried beef.", "Roll chicken breasts and put a slice of bacon around each one.", "Put in pan.", "Mix cream of chic
ken soup (don\'t add water) and sour cream.", "Pour over chicken and sprinkle with paprika.", "Cook for 3 hours, covered, at 300\\u00b0 (last
30 minutes, uncovered).", "If you warm over, warm it slow."] Gathered ["chicken breasts", "bacon", "beef", "cream of chicken soup", "sour crea
m", "paprika"]',
       '["1 can cream of chicken soup", "1 (16 oz.) carton sour cream", "6 chicken breasts (boneless)", "1 pkg. bacon", "1 jar Hormel chipped
beef"] Bacon Wrapped Chicken ["Lay chipped beef on bottom of pan.", "Wrap bacon around chicken breasts.", "Mix sour cream and chicken soup; po
ur over chicken.", "Bake at 250\\u00b0 for 3 hours."] Gathered ["cream of chicken soup", "sour cream", "chicken breasts", "bacon", "beef"]'],
      dtype=object)
```

5. IMPACT OF THE MODEL

As mentioned before, our system makes the smart home personal assistant more smart by helping the residents in their daily food selection process and improving the quality of their lives, especially for foodies who cannot spend time on daily menu selection or don't have the skills for search different food menus.

6. FUTURE SCOPE

we found this field is very vast and there is high scope for improvement and research. Below are some ideas.

- The recommendation system prediction capacity can be improved further by adding other recommendation systems like cooccurrence recommendation systems, FP-growth etc. A combination of NLP base recipe similarity prediction systems along with user-to-user recommendation systems will take this application to the next level.

- Developing a complimentary recommendation system as an addition to the existing model can help the users to get a full-filled menu. For example, along with tacos making limonoid or Biryani with raita etc.

- By adding models to predict the time the user takes to repeat a particular item, the system can predict how frequently a user wants to repeat a particular dish or particular ingredients-based dish and suggest them accordingly.

ACKNOWLEDGMENTS

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REFERENCES

[1] Yashar Deldjoo, Fatemeh Nazary, Arnau Ramisa, Julian Mcauley, Giovanni Pellegrini, Alejandro Bellogin & Tommaso Di Noia, A Review of Modern Fashion Recommender Systems, https://arxiv.org/pdf/2202.02757.pdf

[2] Nusrat Jahan Prottasha, Abdullah As Sami, Md Kowsher, Saydul Akbar Murad, Anupam Kumar Bairagi, Mehedi Masud, and Mohammed Baz, Transfer Learning for Sentiment Analysis Using BERT Based Supervised Fine-Tuning, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9185586/

[3] Vishnu Nandakumar, Recommendation system using BERT embeddings, https://medium.com/analytics-vidhya/recommendation-system-using-bert-embeddings-1d8de5fc3c56

[4] D. Viji, and S. Revathy, A hybrid approach of Weighted Fine-Tuned BERT extraction with deep Siamese Bi – LSTM model for semantic text similarity identification, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8735740/

[5] Xingyun Xie, Zifeng Ren, Yuming Gu and Chengwen Zhang, Text Recommendation Algorithm Fused with BERT Semantic Information, https://dl.acm.org/doi/abs/10.1145/3507548.3507582

[6] Itzik Malkiel , Dvir Ginzburg, Oren Barkan, Avi Caciularu, Jonathan Weill, Noam Koenigstein, Interpreting BERT-based Text Similarity via Activation and Saliency Maps, https://dl.acm.org/doi/abs/10.1145/3485447.3512045

[7] Allyson Ettinger, What BERT Is Not: Lessons from a New Suite of Psycholinguistic Diagnostics for Language Models. https://direct.mit.edu/tacl/article/doi/10.1162/tacl_a_00298/43535/What-BERT-Is-Not-Lessons-from-a-New-Suite-of

[8] Semantic Similarity with BERT, https://keras.io/examples/nlp/semantic_similarity_with_bert/#inference-on-custom-sentences

[9] James Briggs, BERT For Measuring Text Similarity, https://towardsdatascience.com/bert-for-measuring-text-similarity-eec91c6bf9e1

[10] PAUL MOONEY , RecipeNLG (cooking recipes dataset, https://www.kaggle.com/code/paultimothymooney/explore-recipe-nlg-dataset

[11] Kashish Ahuja, Mukul Goel, Sunil Sikka, and Priyanka Makkar, What-To-Taste: A Food Recommendation System, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3670234

[12] Yasmin Beij, A Literature Review on Food Recommendation Systems to Improve Online Consumer Decision-Making, https://edepot.wur.nl/526224
[13] Luís Rita, Building a Food Recommendation System, Towards data science, https://towardsdatascience.com/building-a-food-recommendation-system-90788f78691a
[14] Thi Ngoc Trang Tran, Müslüm Atas, Alexander Felfernig, and Martin Stettinger , Journal of Intelligent Information Systems volume 50, pages 501–526 (2018), An overview of recommender systems in the healthy food domain, https://link.springer.com/article/10.1007/s10844-017-0469-0
[15] Pratiksha Ashok.Naik, International Journal of Innovative Science and Research Technology, ISSN No:-2456-2165, Volume 5, Issue 8, August – 2020
[16] Florian Pecune1*, Lucile Callebert1 and Stacy Marsella1, Designing Persuasive Food Conversational Recommender Systems With Nudging and Socially-Aware Conversational Strategies, https://www.frontiersin.org/articles/10.3389/frobt.2021.733835/full

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