Product Review Summarization

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Problem



Frito Lay Fun Times Mix Variety Pack,		Lay's Potato Chip Variety Pack, 1	Ruffles Potato Chips Variety Pack, 4	
40 Count		Ounce (Pack of 40)	Count (Pack of 1)	
Fun Times Mix	40 Count (Pack of 1)	1 Ounce (Pack of 40)	40ct Variety Pack	40 Count (Pack of 1)
★★★★☆ ~ 163,736		★★★☆ ~ 36,665	★★★★ ~ 12,098	
20K+ bought in past month		20K+ bought in past month	7K+ bought in past month	
\$21 ⁸⁶ (\$21.86/Count)		\$15 ²⁸ Typical: \$19.64	\$23 ²⁹ (\$0.58/Count)	

- Reading reviews = lots of time, not efficient
- Information overload when making purchase decisions using product reviews

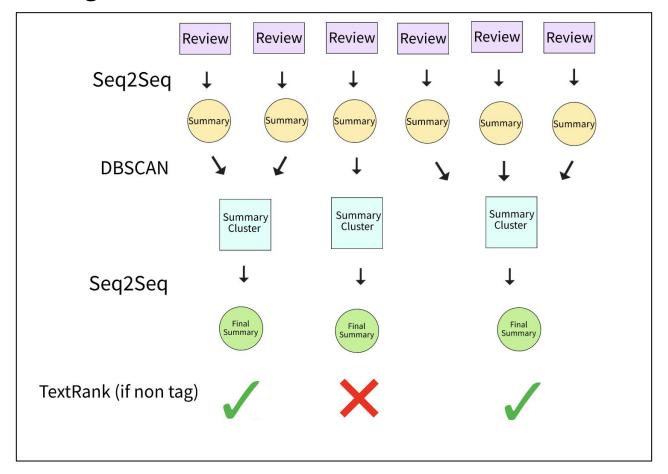
Motivation

- Develop an application that can automatically summarize product reviews
- Save people's time by providing concise summaries, extracting key sentiments, and generating product-specific tags

Our Approach

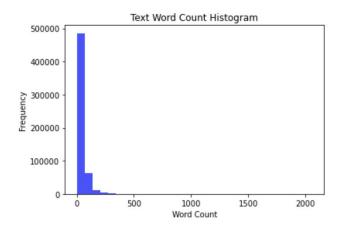
- 2 types of summaries for a product: sentences and tags
 - sentences: a few short sentences describing the product
 - tags: important aspects of the product
- No available dataset for this goal, creative approach:
 - 1. Lots of reviews
 - 2. Summarize each review
 - 3. Group/cluster summaries
 - 4. Re-summarize clustered summaries

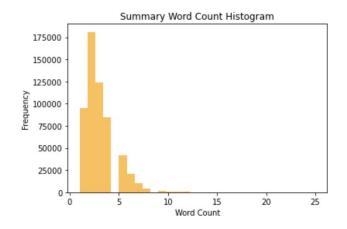
E2E flow diagram



Data + Preprocessing

- Dataset: Amazon Fine Food Reviews
 - Mainly food items
 - ~500,000 rows of reviews + metadata
- Preprocessing:
 - removing stop words + punctuation
 - lowercasing
 - adding tokens (SOS, EOS)
- Filtering:
 - max text length = 150 tokens
 - max summary len=12 tokens
- Dataset Subsetting:
 - two different output types = train on different data
 - sentence model: min summary len>= 3 tokens
 - tag model: min summary len <= 3 tokens





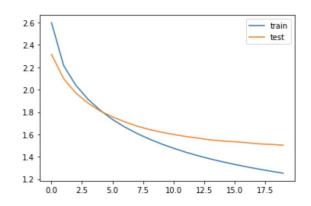
Model + Training

- For tokenizers, excluded rare words
- Seq2Seq model
 - LSTM based encoder-decoder architecture
 - attention layer
 - optimizer: rprop
 - loss: sparse categorical cross entropy
- Total params: ~19 million
- Inference:
 - Decoding Process: Utilizes the trained model to decode each review into a summary, word by word.
 - Attention Mechanism: Focuses on relevant parts of each review for meaningful summarization.

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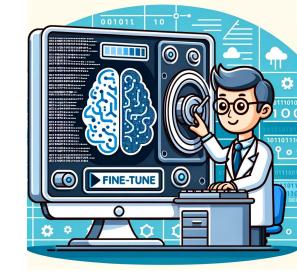
Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 150)]	0	
embedding (Embedding)	(None, 150, 100)	5815400	input_1[0][0]
lstm (LSTM)	[(None, 150, 300), (481200	embedding[0][0]
lstm_1 (LSTM)	[(None, 150, 300), (721200	lstm[0][0]
input_2 (InputLayer)	[(None, None)]	0	
lstm_2 (LSTM)	[(None, 150, 300), (721200	lstm_1[0][0]
embedding_1 (Embedding)	(None, None, 100)	1397900	input_2[0][0]
lstm_3 (LSTM)	[(None, 150, 300), (721200	lstm_2[0][0]
lstm_4 (LSTM)	[(None, None, 300),	481200	embedding_1[0][0] lstm_3[0][1] lstm_3[0][2]
attention_layer (AttentionLayer	((None, None, 300),	180300	lstm_3[0][0] lstm_4[0][0]
concat_layer (Concatenate)	(None, None, 600)	0	lstm_4[0][0] attention_layer[0][0]
time_distributed (TimeDistribut	(None, None, 13979)	8401379	concat_layer[0][0]

Total params: 18,920,979 Trainable params: 18,920,979 Non-trainable params: 0



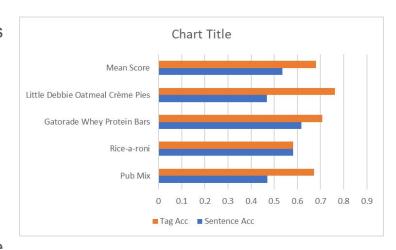
Fine Tuning

- different amount of LSTM layers
- different embedding dimensions
 - higher = better, but limited by Kaggle's memory + GPU quota
- smaller batch sizes
- different dropout values:
 - too low = model more likely to copy/reuse what original label is
 - too high = model more likely to output very broad summaries (good product)
 - had to find a good balance (0.2-0.3 range)
- Training two different models
 - one on shorter summaries for tags, one on longer summaries for sentences

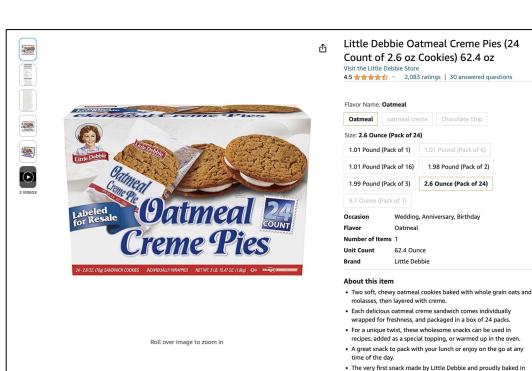


Results + Evaluation

- we use word embedding similarity as our metric
 - effective metric for comparing summaries and tags because it captures semantic relationships between words
- for tag output, our mean score is 0.681
- for sentence output, our mean score is
 0.534
- drawbacks:
 - not enough reviews (we ideally need ALL of the reviews for the product we are evaluating)
 - not enough different products (bottleneck was time since we had to manually collect)



Example Output



the USA since 1960.

Amazon summary:



Our sentence summary:

'Healthy tasty snack. Best cookie ever.'

Our tag summary:

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['great taste', 'good value', 'great product',
'good', 'best', 'great value']
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Future Work

- larger evaluation dataset
- different dataset
- apply to other types of reviews
 - service
 - restaurant
 - location

Thanks for listening!