Weakly-Supervised Opinion Summarization by Leveraging External Information

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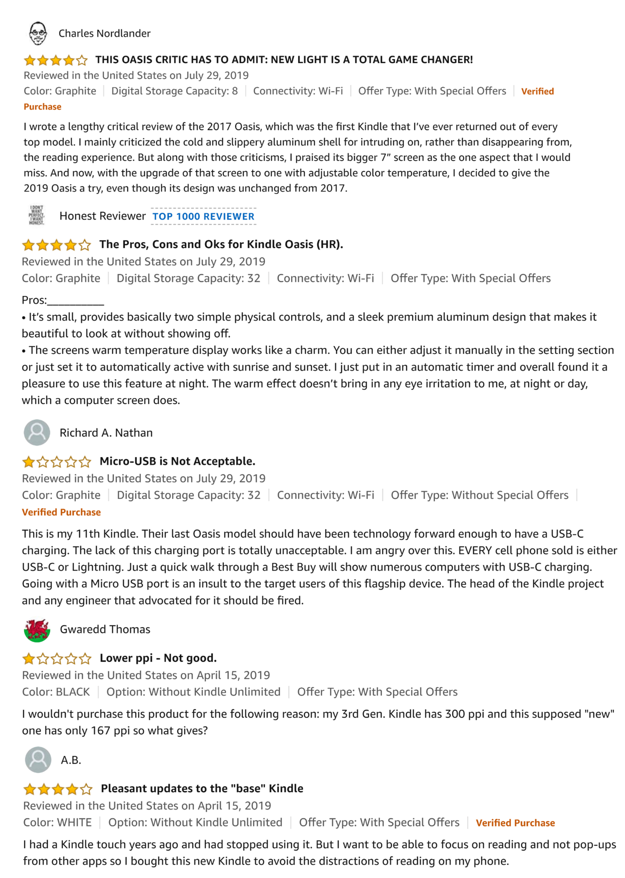
Overview

Opinion summarization from online product reviews is a challenging task involving identifying opinions related to various aspects of the product. In this work,

- We address this task without human supervision – by incorporating domain knowledge from external information;
- We propose AspMem, a generative approach for aspect identification that can use such knowledge effectively;
- We adopt a three-step pipeline to create summaries by identifying aspects, computing salience, and selecting opinions.

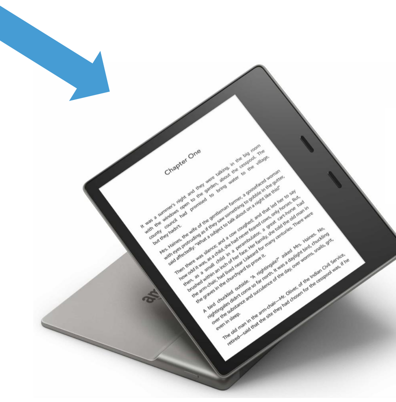
Task Description

Customer Reviews



Feature descriptions

- Our best 7", 300 ppi flush-front Paperwhite display.
- Adjustable warm light to shift screen shade from white to amber.
- Waterproof (IPX8) so you can read in the bath or by the pool.
- Thin and light ergonomic design with page turn buttons.
- Reads like real paper with the latest e-ink technology for fast page
- Instant access to millions of books, newspapers, and audiobooks.
- Works with Audible - pair with Bluetooth headphones or speakers to switch seamlessly between reading and listening.
- A single battery charge lasts weeks, not hours.



Review Summary

It looks and feels much **bigger** than you'd think. The **storage capability** is great. More storage, more books! **Lighting to adaptive** with 2 ambient sensors. One HUGE improvement is that the Oasis is **waterproof**! Overall it's a great e-reader, but abysmal **battery life** negates all the positive features. Shorter than Voyage or Original Oasis. Significantly short. Also, one cannot follow text with **audio**.

Aspect Identification

AspMem contains an array of memory cells $\mathcal{A} = \{a_1, a_2, \cdots, a_k\}$ to store aspect-related information. Similar to topic models, we assume the review segment s is generated from these aspect (topic) memories.

Sentence Representation

$$P(v_i|a_j) \propto \exp(\cos(\boldsymbol{v}_i, \boldsymbol{a}_j)),$$
$$P(v_i) = \sum_j P(v_i|a_j)P(a_j),$$
$$z_i = \frac{P(v_i)}{\sum_j P(v_j)}, \quad \boldsymbol{s} = \sum_i z_i \boldsymbol{v}_i.$$

Sentence Generation

$$P(s|a_i) \propto \exp(\cos(\boldsymbol{s}, \boldsymbol{a}_i)).$$

Likelihood Maximization

$$J(\theta) = -\sum_{s \in \mathcal{X}} \log P(s; \boldsymbol{\theta}) + \lambda \left\| \hat{\mathbf{A}}\hat{\mathbf{A}}^{\mathbf{T}} - \mathbf{I} \right\|_2.$$

Aspect Prediction

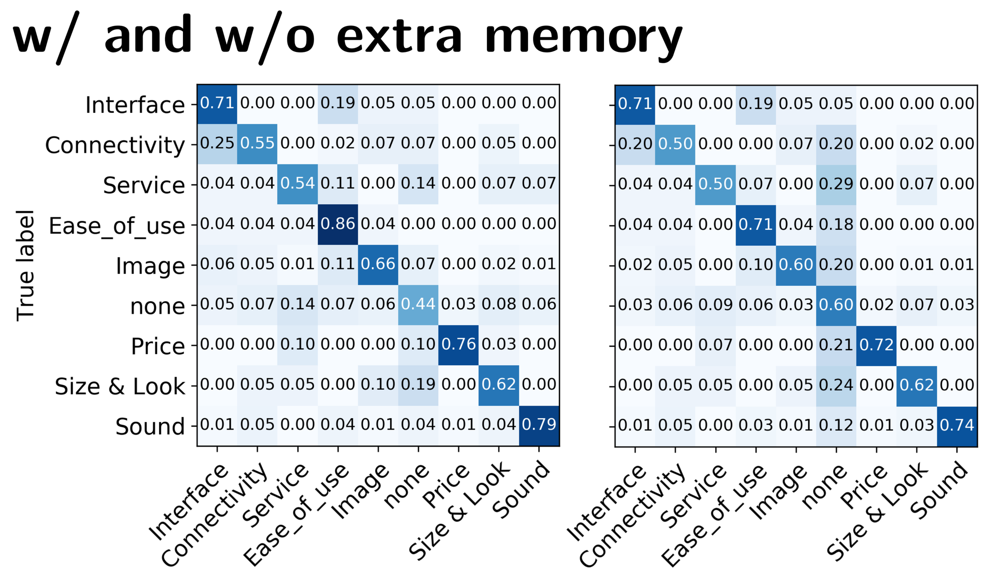
$$P(a_i|s) \propto P(s|a_i)P(a_i).$$

Results

Evaluated by multi-label micro F_1

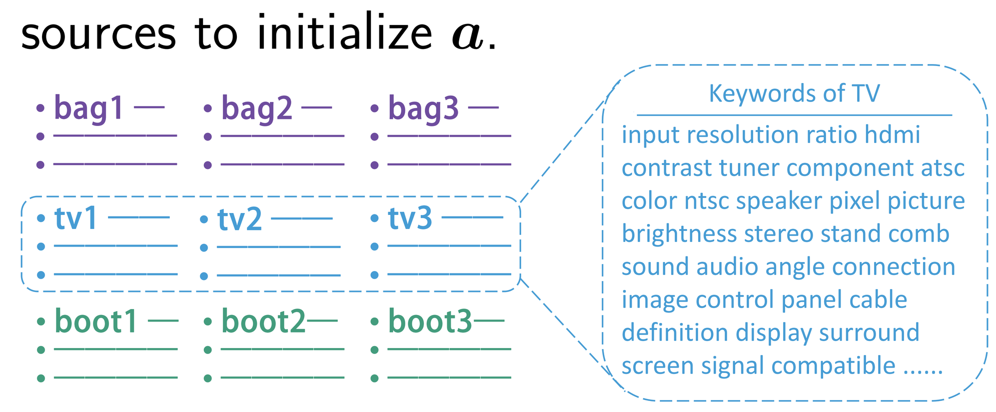
Model	Bags	B/T	Boots	Keyb/s	TVs	Vacs	Ave.
ABAE (2017)	41.6	48.5	41.0	41.3	45.7	40.6	43.2
MATE (2018)	48.6	54.5	46.4	45.3	51.8	47.7	49.1
BERT (2019)	**61.4**	**66.5**	52.0	57.5	**63.0**	60.4	**60.2**
AspMem	52.4	58.1	54.5	51.4	53.9	54.6	54.2
w/ extra mem	60.0	62.0	**55.8**	**61.8**	60.0	**61.8**	**60.2**

w/ and w/o extra memory



External Information

Rather than estimating the aspect memory $\boldsymbol{a}$ by human-annotated data or unsupervised methods, we select the top K keywords with the highest TF-IDF value from external resources to initialize $\boldsymbol{a}$.



Salience Computation

Relevance

✔ "It looks and feels much bigger."

✘ "I love this one!"

$$\mathbb{S}_{rel}(s) = \frac{1}{|s|} \sum_i \max_{j=\{1,\cdots,K\}} g(\cos(\boldsymbol{v}_i, \boldsymbol{a}_j) \cdot w_j).$$

Sentiment

✔ "The storage is great!"

✘ "Bought it for my daughter."

$$\mathbb{S}_{senti}(s) = \mathbf{p}^T \text{softmax}(\text{MLP}(\text{LSTM}(s)))$$

Overall

$$\mathbb{S}_{sal}(s) = \mathbb{S}_{rel}(s) \times \mathbb{S}_{senti}(s).$$

Opinion Selection

An ideal summary would contain high-salience opinions, avoid redundant information, and meet the limit on the length. These goals can be formalized as an ILP problem:

$$\boldsymbol{\alpha} = \arg\max_{\boldsymbol{\alpha}} \sum_i \mathbb{S}_{sal}(s_i)\alpha_i - \sum_{i,j} sim_{ij}\beta_{ij},$$

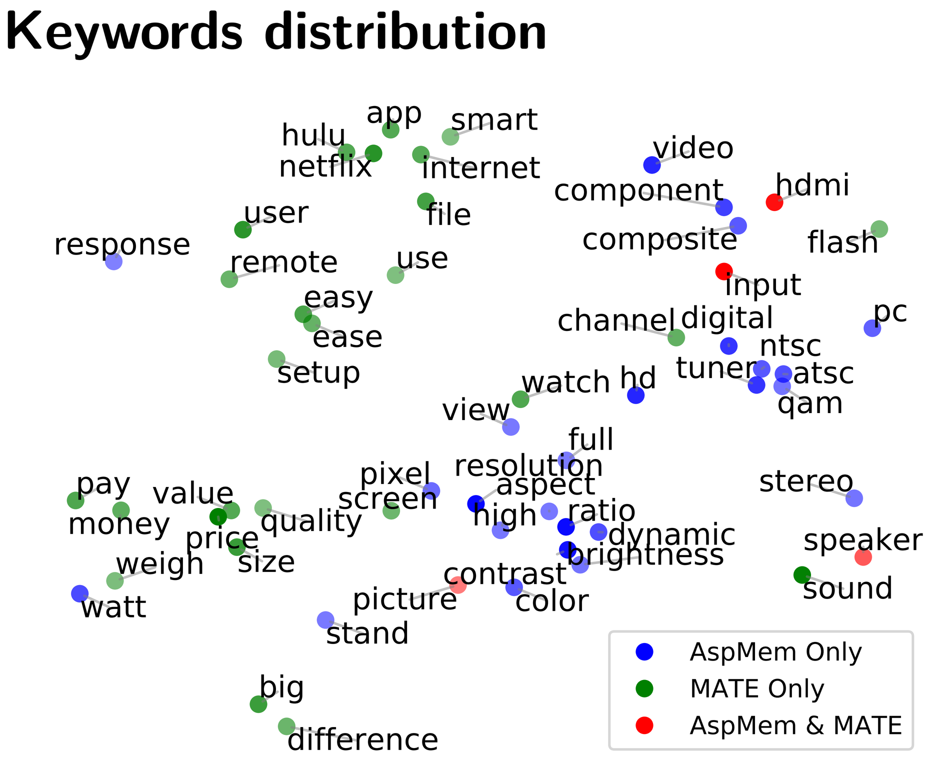
$$\begin{aligned} s.t. \quad & \alpha_i, \beta_{ij} \in \{0,1\} && \forall i,j \\ & \beta_{ij} \geq \alpha_i + '\alpha_j - 1 && \forall i,j \\ & \beta_{ij} \leq \frac{1}{2}(\alpha_i + \alpha_j) && \forall i,j \\ & \textstyle\sum_i \alpha_i l_i \leq L && \forall i \end{aligned}$$

Results

Evaluated by Rouge

Methods	R-1	R-2
Lead	35.5	15.2
LexRank	37.7	14.1
MATE + MILNET [1]	44.1	21.8
AspMemSum	46.6	25.7
w/o filtering	**48.0**	**28.7**
w/o Relevance	41.5	20.5
w/o Sentiment	40.5	18.2
w/o ILP	46.2	25.1
Inter-annotator Agreement	54.7	36.6

Keywords distribution



Summary examples

So this is the **perfect size**. The **padding** is good and it is quite **stylish**. there is just **enough size** for a mouse, power cord, a fre CD's and a cell phone. **Functionality** wise : awesome! The **price** on Amazon is great. Unfortunately over the holidays the **hand strap broke**. As I stated above, getting the **computer** in and out is pain.

Fantastic **sound, great fit** and a simple practicle **set up**. i find this device very good. And with the additional purchase of some acustibud ear pieces the **sounds** is quite good. This is an awesome product. The **design** of the ear pieces **did not fit my ear** anatomy very well. the **sound** isn't as rich as other on ear Bluetooth.

[1] Angelidis, S., Lapata, M. (2018). Summarizing Opinions: Aspect Extraction Meets Sentiment Prediction and They Are Both Weakly Supervised. In EMNLP 2018.

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github.com/zhaochaocs/AspMem