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Training Neural Networks for Aspect Extraction Using Descriptive Keywords Only

Giannis Karamanolakis Columbia University gkaraman@cs.columbia.edu

Daniel Hsu Columbia University djhsu@cs.columbia.edu

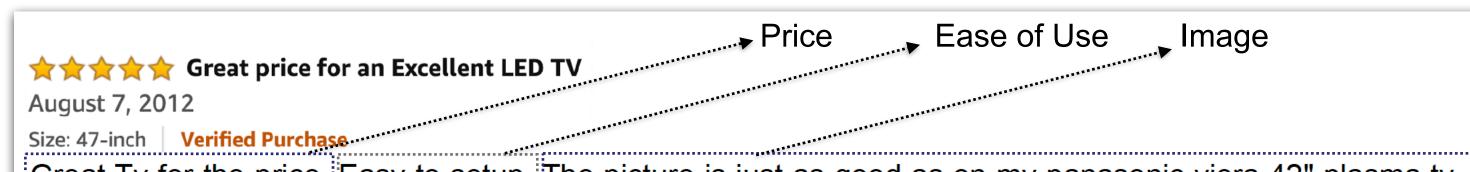
Luis Gravano Columbia University gravano@cs.columbia.edu

LIMITED DATA

ICLR 2019

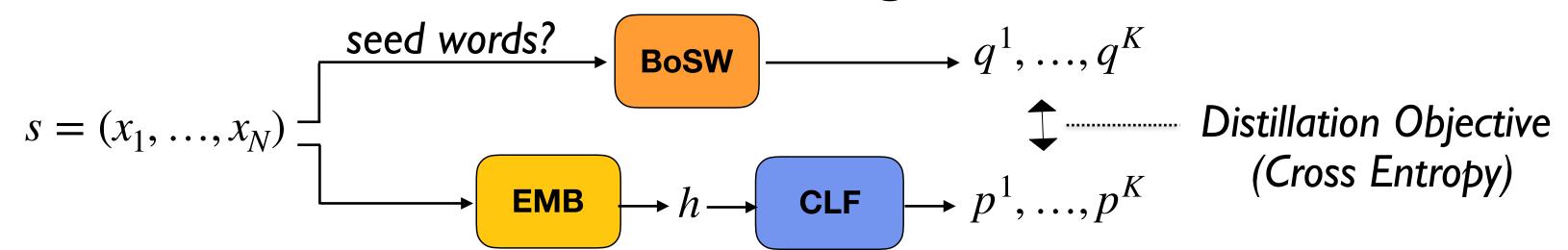
Aspect Extraction in Online Product Reviews

Goal: Identify which product **aspects** (e.g., price, quality) are discussed in individual **segments** (e.g., sentences, clauses) of the product's reviews. Key task in: Sentiment Analysis, Opinion Mining, Review Summarization.

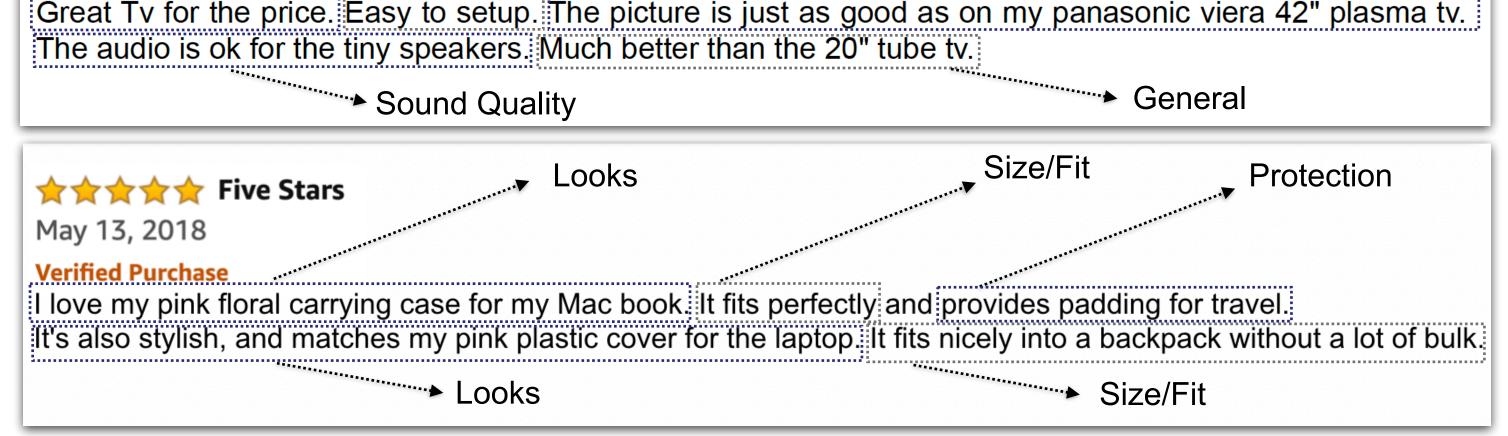


Our Weakly Supervised Approach

A teacher-student framework for training neural networks.



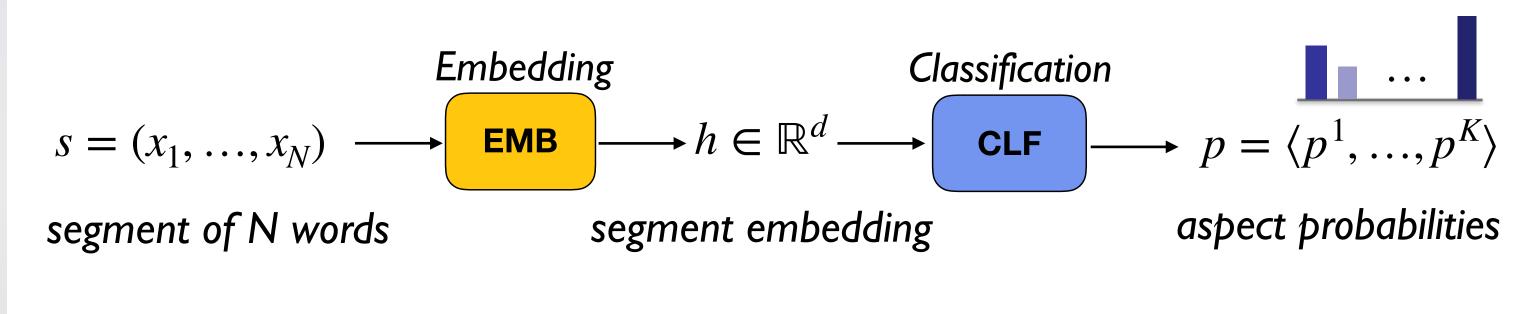
• **Teacher**: A bag-of-seed-words (BoSW) logistic regression classifier



Neural Networks For Aspect Extraction

I. Supervised

Deep neural networks learn good representations of text for classification.



- Binary weights: "if a seed word appears, increase the corresponding aspect score."

The teacher only considers the (few) seed words.

• **Student:** An embedding-based neural network

- Mimics the teacher's predictions (distillation loss).
- Encouraged to generalize via regularization (L2 + dropout).

The student also considers the (many) non-seed words.

Example 1: ... For fifty bucks, it was a great deal... Example 2: ... The picture looks very pixelated when playing bluray movies...

(0 seed words) (2 seed words)

- Experiment: We completely drop seed words (DSW) from the student's input.

Example 2: ... The UNK UNK very pixelated when playing bluray movies...

We effectively leverage a few seed words as supervision for training neural networks.

Experiments

Datasets

• Amazon product reviews

Average performance across 6 domains

Issue: Ground-truth aspect labels are not inherently available.

• Manual segment annotation is expensive and not scalable.

<u>2. Unsupervised (Neural Topic Models)</u>

Aspect Based Auto Encoder (ABAE) [He et al. '17]

$$s \longrightarrow \texttt{EMB} \longrightarrow h \longrightarrow \texttt{CLF} \longrightarrow p^1, \dots, p^K \longrightarrow h' = \sum_{k=1}^K p^k A^k \qquad A^K$$

• Aspect embeddings $A^k \in \mathbb{R}^d$ initialized using **k-means**.

Issue: ABAE fails to capture the particular aspects of interest.

• Probabilities p^1, \dots, p^K are **not** mapped to the K aspects of interest.

3. Weakly Supervised

Idea: Use seed words as a "weak" source of supervision.

• Seed words: descriptive keywords. Aspect • Assume ~30 seed words per aspect are available. Price • Easier to collect than thousands of labels.

Seed Words price, value, money, ... Image | picture, color, quality, ...

 A^{K}

. . .

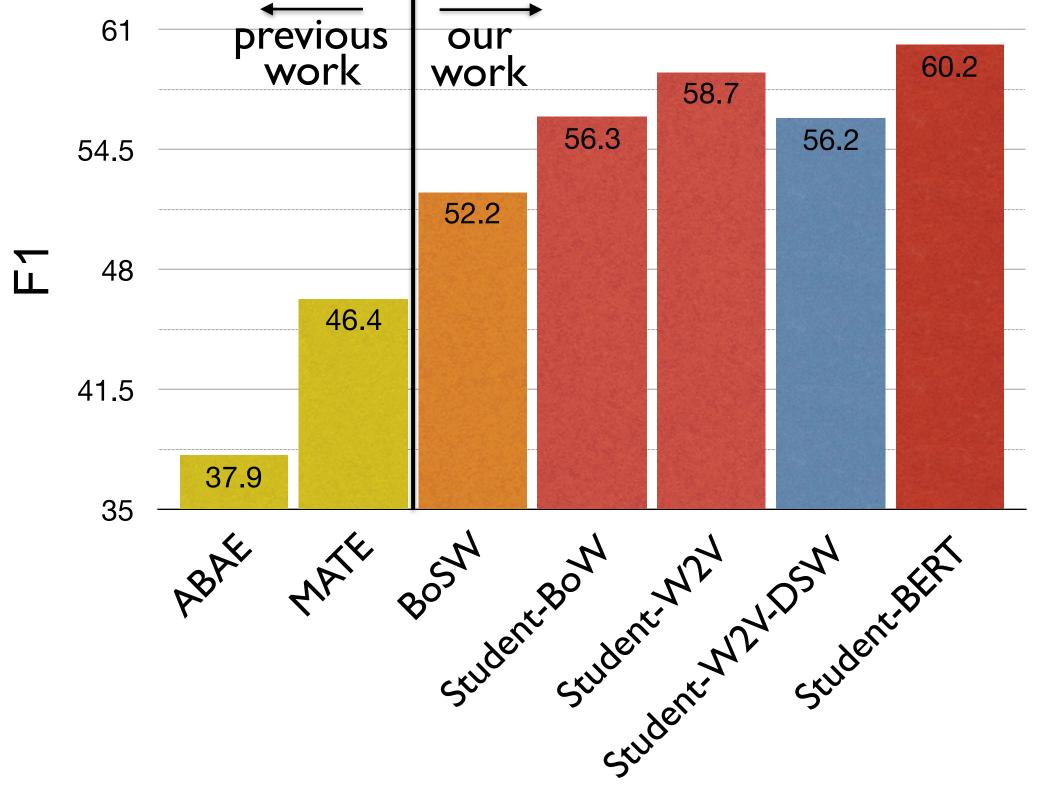
- 6 product domains
- •9 aspects per domain
- 30 seed words per aspect

Segment Embedding

- **BoW:** bag-of-words representation • W2V: avg of word2vec embeddings
- **BERT:** Google's BERT (avg pooling)

Results

- BoSW outperforms MATE using only seed words.
- **Student-BoW/Student-W2V** outperform **BoSW** with proper regularization.
- **Student-W2V** associates non-seed words to aspects: even when dropping the seed words from the student's input (Student-W2V-DSW) it outperforms BoSW.
- **Student-BERT** outperforms MATE by 30%.



Conclusions & Future Work

•Seed words are effectively leveraged into BoW classifiers.

• **BoW classifiers** are used in a distillation framework to train **neural networks**.

• Student generalizes better than teacher: associates non-seed words with aspects.

• On-going work: handling **noisy** seed words & learning **better** seed words.

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Multi-seed Aspect Extractor (MATE) [Angelidis & Lapata '18] • Extends ABAE. • Aspect embeddings A^k initialized using seed words.

• A^k : average of seed word embeddings.

Question: Does MATE effectively leverage the seed words? • Seed words are used just for the **initialization** of aspect embeddings.