

UGSD:

User Generated Sentiment Dictionaries from Online Customer Reviews

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CFDA-CLIP
Labs



Source Code:
UGSD

Motivation

- ✓ Constructing domain-specific sentiment dictionaries is important to sentiment analysis.
- ✓ Customer review platforms attain rich information about the ways that people convey their sentiment in certain domains.
- ✓ General sentiment dictionaries or annotated seed words greatly impact the results of dictionary construction.

Contributions

- ✓ Data-driven dictionary: Requiring no additional annotation of seed words or external dictionaries.
- ✓ Domain-specific dictionaries: Applying to a variety of user-generated content from different domains.
- ✓ Application scalability: Producing representations of the learned sentiment words during the dictionary construction.

Experiments

Table 4: Performance on sentiment classification

	Yelp		TripAdvisor		Amazon	
	# word	F1 Acc	# word	F1 Acc	# word	F1 Acc
NLTK	6,787	0.762 0.697	6,787	0.759 0.699	6,787	0.766 0.707
MPQA	6,450	0.708 0.601	6,450	0.701 0.608	6,450	0.716 0.616
SentiWordNet	24,123	0.675 0.534	24,123	0.670 0.520	24,123	0.685 0.551
Stanford Yelp	2,005	0.682 0.534	2,005	0.686 0.544	2,005	0.679 0.530
$\mathcal{G}_{\max}(\cdot)$	$\mathcal{L}_{r_5} \cup \mathcal{L}_{r_1}$	1,524 0.733 0.755	1,888 0.664 0.679	717 0.744 0.727		
	$\mathcal{L}_{r_{45}} \cup \mathcal{L}_{r_{12}}$	2,692 0.771 0.777	3,428 0.746 0.753	1,566 0.763 0.755		
$\mathcal{G}_{z>1.2}(\cdot)$	$\mathcal{L}_{r_5} \cup \mathcal{L}_{r_1}$	364 0.784 0.758	710 0.726 0.630	189 0.801 0.782		
	$\mathcal{L}_{r_{45}} \cup \mathcal{L}_{r_{12}}$	451 0.792 0.762	1,060 0.736 0.650	346 0.800 0.772		

Table 5: Performance on entity ranking

	TripAdvisor		Amazon	
	# word	NDCG@5 NDCG@10	# word	NGCG@5 NDCG@10
Frequency	-	0.610 0.664	-	0.494 0.623
NLTK	1,071	0.556 0.632	595	0.603 0.659
MPQA	1,294	0.562 0.641	710	0.571 0.654
SentiWordNet	4,522	0.442 0.530	2,207	0.543 0.574
$\mathcal{G}_{\max}(\cdot)$	\mathcal{L}_{r_5}	207 0.794 0.818	258 0.635 0.712	
	$\mathcal{L}_{r_{45}}$	745 0.669 0.724	493 0.549 0.641	
	$\mathcal{L}_{r_{345}}$	1,626 0.654 0.698	995 0.574 0.655	
$\mathcal{G}_{z>1.2}(\cdot)$	\mathcal{L}_{r_5}	288 0.782 0.807	51 0.606 0.695	
	$\mathcal{L}_{r_{45}}$	569 0.735 0.770	114 0.515 0.631	
	$\mathcal{L}_{r_{345}}$	895 0.719 0.751	221 0.515 0.627	

Our framework: UGSD

Review transformation



★★★★★
Romantic Eiffel Towel. Well_worth paying the extra to get to the top for ...
★★★★★
The Eiffel Towel is an overrated land mark and was overpopulated with tourists ...
★★★★★
Very_disappointing. Lines were crazy, people trying to get you to buy ...

- ✓ Leverage POS information
- ✓ Concatenate adverbs and adjectives
- ✓ Replace entities with ratings

Representation learning

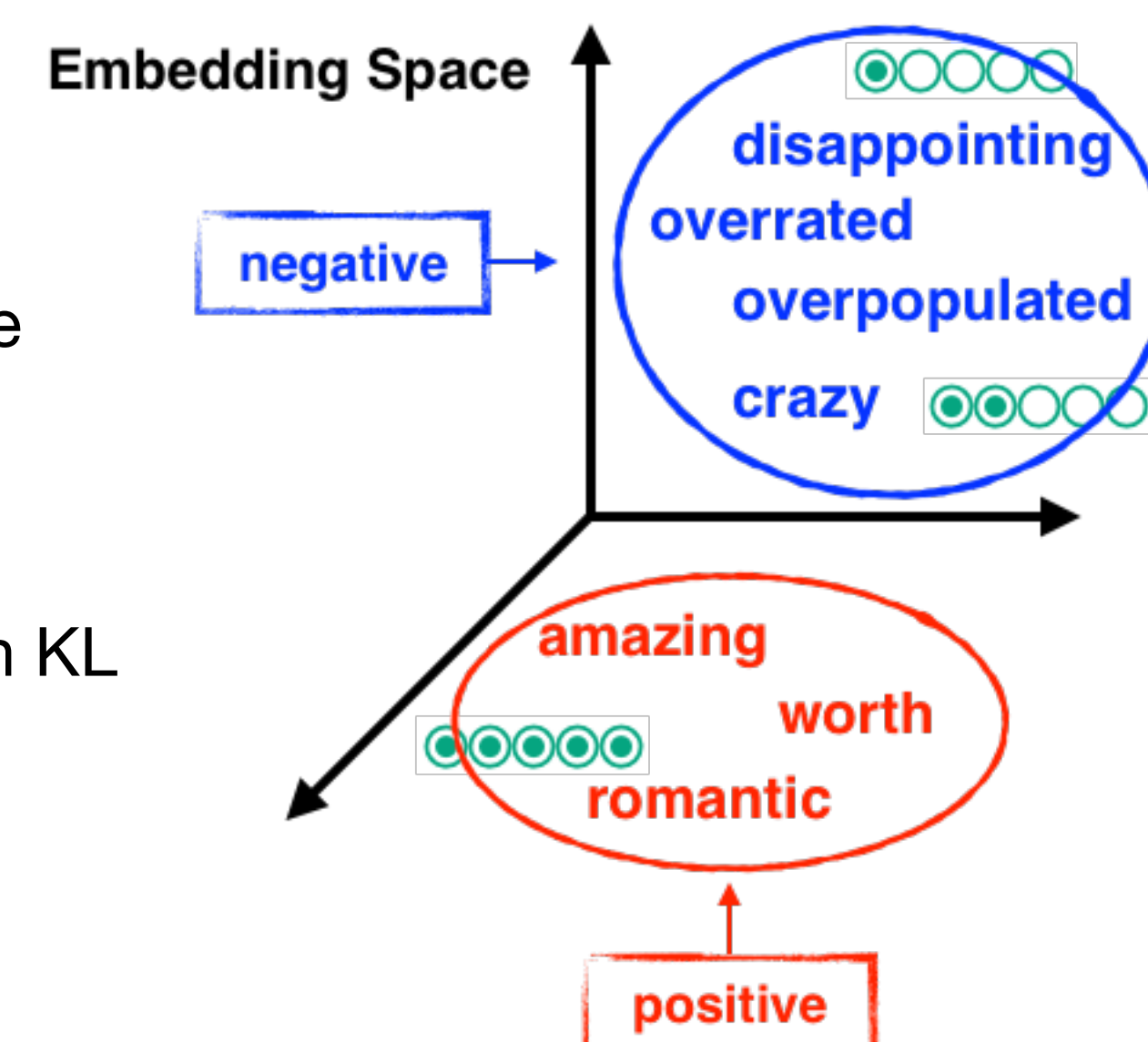
- ✓ Joint probability between words
- ✓ Minimize the distance between the empirical and learned distribution

$$p(i, j) = \frac{1}{1 + e^{-\vec{v}_i^T \cdot \vec{v}_j}}$$

$$O = \text{dist}(\hat{p}(\cdot, \cdot), p(\cdot, \cdot))$$

- ✓ Replace the distance function with KL divergence

$$O = - \sum_{(i, j) \in A} f_{ij} \log p(i, j)$$



Dictionary construction

- ✓ Maximum-cosine-similarity scheme:

$$m_i = \max_{1 \leq j \leq |\mathcal{R}|} a_{ij}$$

$$\mathcal{G}_{\max}(A) = (b_{ij}) = (1_{\{a_{ij} \geq m_i\}}) \in \mathbb{R}^{|\mathcal{S}| \times |\mathcal{R}|}$$
- ✓ Z-score scheme:

$$z_{ij} = (a_{ij} - \mu_j) / \sigma_j$$

$$\mathcal{G}_{z>\ell}(A) = (b_{ij}) = (1_{\{z_{ij} > \ell\}}) \in \mathbb{R}^{|\mathcal{S}| \times |\mathcal{R}|}$$

Amazon dictionaries

Top	\mathcal{L}_{r_5}	$\theta_s^{r_5}$	\mathcal{L}_{r_4}	$\theta_s^{r_4}$	\mathcal{L}_{r_3}	$\theta_s^{r_3}$	\mathcal{L}_{r_2}	$\theta_s^{r_2}$	\mathcal{L}_{r_1}	$\theta_s^{r_1}$
1	wonderful	0.599	not_perfect	0.695	okay	0.813	unfortunate	0.785	extremely_disappointed	0.769
2	wonderfully		overall	0.600	ok	0.605	unfortunately		worthless	0.740
3	fantastic	0.538	standalone	0.525	alright	0.583	not_good	0.626	not_new	0.631
4	amazing	0.532	nice	0.503	not_bad	0.521	disappointed	0.579	disappointing	
5	really_great	0.526	good	0.469	dumb	0.517	not_waterproof	0.542	worse	0.609
6	great	0.503	almost_perfect	0.449	not_great	0.418	really_disappointed	0.516	far_worst	0.594
7	lovely	0.428	lightest	0.312	decent	0.399	really_disappointing		unacceptable	0.589
8	excellent	0.406	far_satisfied	0.290	temporary	0.386	unreliable	0.508	totally_useless	0.583
9	best	0.369	little	0.284	otherwise	0.375	dissappointed	0.508	useless	0.578
10	absolutely_wonderful	0.347	starter	0.281	pretty_decent	0.346	not_happy	0.400	faulty	0.576
11	excellent	0.319	great	0.265	not_smooth	0.297	sad	0.409	not_acceptable	0.568
12	happy	0.315	pretty_happy	0.257	bland	0.290	not_happier		lemon	0.531
13	really_loving	0.297	solid	0.256	not_happy	0.283	not_happier	0.389	dissatisfied	0.527
14	smart	0.290	graphically_intense	0.238	not_happier		unbearable	0.386	not_happy	0.524
15	ever	0.271	not_primary	0.220	not_crazy	0.276	not_worst	0.386	not_happier	
16	absolute	0.263	uncertain	0.219	really_annoying	0.271	absolutely_terrible	0.370	apparent	0.514
17	totally_satisfied	0.258	not_expensive	0.199	beloved	0.265	unhappy	0.367	apparently	0.512
18	bought	0.251	still_amazing	0.194	really_excellent	0.248	astonishing	0.359	defective	0.512
19	beautiful	0.242	darn	0.165	wise	0.247	amazing	0.359	miserable	0.509
20	perfect	0.225	not_smart	0.163	inaccurate	0.236	frustrated	0.339	miserably	0.509