自然语言处理

情感分析

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主要内容

- 情感分析定义
- 情感分析的应用
- 基于朴素贝叶斯方法的情感分析
- 基于CNN的情感分析
- 情感分析中的新任务

情感分析定义

- 情感分析：” 态度”检测（ the detection of **attitudes** ）
  - 情感分析结果包含4个要素：情感持有者, 情感目标, 极性, 辅助信息>
    - – 持有者（Holder）: who expresses the sentiment
    - – 目标（Target）: what/whom the sentiment is expressed to
    - – 极性（Polarity）: the nature of the sentiment (positive, negative, or neutral)
    - – 辅助信息（Auxiliary）: strength, summary, confidence, time

情感分析示例

- Sentiment := <**Holder**, Target, Polarity, Auxiliary>
  - **Holder:** who expresses the sentiment
  - Target: what/whom the sentiment is expressed to
  - Polarity: the nature of the sentiment (e.g., positive/negative)
- *In his recent State of the Union address,* ***US President Bush*** *quite unexpectedly labeled Iran, Iraq, and the DPRK as an "axis of evil".*

↓

Negative

情感分析的任务

- Simplest task:
  - Is the attitude of this text positive or negative?
- More complex:
  - Rank the attitude of this text from 1 to 5
- Advanced:
  - Detect the target, source, or complex attitude types

简单任务举例：电影评论情感分析

- Polarity detection:
  - Is an IMDB movie review positive or negative?
- Data: *Polarity Data 2.0:*
  - http://www.cs.cornell.edu/people/pabo/movie-review-data

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP, 79-86.
Bo Pang and Lillian Lee. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. ACL, 271-278

IMDB影评情感分析数据集样例

✓

when _star wars_ came out some twenty years ago , the image of traveling throughout the stars has become a commonplace image . [...]

when han solo goes light speed , the stars change to bright lines , going towards the viewer in lines that converge at an invisible point .

cool .

october sky offers a much simpler image–that of a single white dot , traveling horizontally across the night sky . [. . .]

X

" snake eyes " is the most aggravating kind of movie : the kind that shows so much potential then becomes unbelievably disappointing .

it' s not just because this is a brian depalma film , and since he' s a great director and one who' s films are always greeted with at least some fanfare .

and it' s not even because this was a film starring nicolas cage and since he gives a brauvara performance , this film is hardly worth his talents .

情感分析的其他名字

- 观点抽取 Opinion extraction
- 观点挖掘 Opinion mining
- 情感挖掘 Sentiment mining
- 主观分析 Subjectivity analysis

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情感分析的应用

- *Movie*: is this review positive or negative?
- *Products*: what do people think about the new iPhone?
- *Public sentiment*: how is consumer confidence? Is despair increasing?
- *Politics*: what do people think about this candidate or issue?
- *Prediction*: predict election outcomes or market trends from sentiment.

面向社会媒体内容的情感分析

London Eye light show to be powered by Olympic tweet positivity

Positive or negative messages on Twitter using the hashtag #Energy2012 will fuel lights on the London Eye throughout the Olympics.

By Sam Byford | @345triangle | Jul 20, 2012, 4:55am EDT

https://www.theverge.com/2012/7/20/3171484/london-eye-lightshow-olympic-tweets

面向产品评论的情感分析

商品详情 规格参数 **累计评价 31443** 手机购买

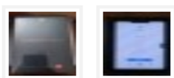
与描述相符
4.9
★★★★★

大家都写到
系统很强大(2863) 手机不错(2810) 款式好看(2724) 手感也很好(1310)
快递不错(1075) 像素挺好(878) 小贵(199)

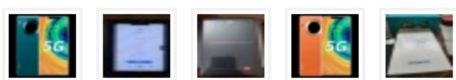
全部 追评 (1746) 图片 (8348) 有内容 按默认

初次评价:
12.17

物流快服好质量好!



收货2天后追加: 好用，用了几天功能蛮可以的，手机买了各种各样的都有用过，感觉华为用得自然安全舒服!



网络类型：5G SA/NSA双模
机身颜色：亮黑色
套餐类型：官方标配
存储容量：8+512GB

t***9（匿名）
超级会员

双十二买的，发货很速度，快递也很给力隔天就到了，手机运行速度没得说，快！拍照超清，我用手机总体还是比较频繁的，电量可以续航一天多没问题！总之这几天的用机体验很好，期待后续发现它更多的便捷优势！更希望咱们华为越来越强大

网络类型：5G SA/NSA双模
机身颜色：翡冷翠
套餐类型：官方标配
存储容量：8+256GB

c***a（匿名）

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基于朴素贝叶斯方法的情感分析

- Tokenization
- Feature Extraction
- Classification using Naïve Bayes

面向情感分析的Tokenization

- Deal with HTML and XML markup
- Twitter mark-up (names, hash tags)
- Capitalization (preserve for words in all caps)
- Phone numbers, dates
- Emoticons

Potts emoticons

```
[<>]?                        # optional hat/brow
[:;=8]                       # eyes
[\-o\*\']?                   # optional nose
[\)\]\(\[dDpP/\:\}\{@\|\\]   # mouth
|                            #### reverse orientation
[\)\]\(\[dDpP/\:\}\{@\|\\]   # mouth
[\-o\*\']?                   # optional nose
[:;=8]                       # eyes
[<>]?                        # optional hat/brow
```

- Useful code:
  - Christopher Potts sentiment tokenizer
  - Brendan O' Connor twitter tokenizer

情感分析中的特征抽取

- Which words to use?
  - Only adjectives
  - All words
    - All words turns out to work better（Pang, 2002)
- How to handle negation
  - `I` **`didn't`** `like this movie`

    vs
  - `I really like this movie`

如何处理否定

Add NOT_ to every word between negation and following punctuation:

```
didn't like this movie , but I
```

```
didn't NOT_like NOT_this NOT_movie but I
```

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference (APFA).
Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

Naïve Bayes回顾

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{w_i \in d} P(w_i | c_j)$$

$$\hat{P}(w \mid c) = \frac{count(w, c) + 1}{count(c) + |V|}$$

Binarized (Boolean feature) Multinomial Naïve Bayes

- Intuition:
  - For sentiment (and probably for other text classification domains)
  - Word occurrence may matter more than word frequency
    - The occurrence of the word *fantastic* tells us a lot
    - The fact that it occurs 5 times may not tell us much more.
  - Boolean Multinomial Naïve Bayes
    - Clips all the word counts in each document at 1

Boolean Multinomial Naïve Bayes: Learning

- From training corpus, extract Vocabulary

- Calculate $P(c_j)$ terms
  - For each c_j in C do

    $docs_j \leftarrow$ all docs with class $=c_j$

$$P(c_j) \neg \frac{|docs_j|}{|\text{total \# documents}|}$$

- Calculate $P(w_k \mid c_j)$ terms
  - $Text_j \leftarrow$ single doc containing all $docs_j$
  - For each word w_k in *Vocabulary*

    $n_k \leftarrow$ # of occurrences of w_k in $Text_j$

$$P(w_k \mid c_j) \neg \frac{n_k + a}{n + a\,|Vocabulary|}$$

Boolean Multinomial Naïve Bayes: Learning

- From training corpus, extract Vocabulary

- Calculate $P(c_j)$ terms
  - For each c_j in C do

    $docs_j \leftarrow$ all docs with class $=c_j$

$$P(c_j) \neg \frac{|docs_j|}{|\text{total \# documents}|}$$

- Calculate $P(w_k \mid c_j)$ terms
  - Remove duplicates in each doc:
    - For each word type w in doc_j
      - Retain only a single instance of w
  - $Text_j \leftarrow$ single doc containing all $docs_j$
  - For each word w_k in *Vocabulary*

    $n_k \leftarrow$ # of occurrences of w_k in $Text_j$

$$P(w_k \mid c_j) \neg \frac{n_k + a}{n + a\,|Vocabulary|}$$

Boolean Multinomial Naïve Bayes on a test document *d*

- First remove all duplicate words from *d*
- Then compute NB using the same equation:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(w_i \mid c_j)$$

Normal vs. Boolean Multinomial NB

Normal	Doc	Words	Class
Training	1	Chinese Beijing Chinese	c
	2	Chinese Chinese Shanghai	c
	3	Chinese Macao	c
	4	Tokyo Japan Chinese	j
Test	5	Chinese Chinese Chinese Tokyo Japan	?

Boolean	Doc	Words	Class
Training	1	Chinese Beijing	c
	2	Chinese Shanghai	c
	3	Chinese Macao	c
	4	Tokyo Japan Chinese	j
Test	5	Chinese Tokyo Japan	?

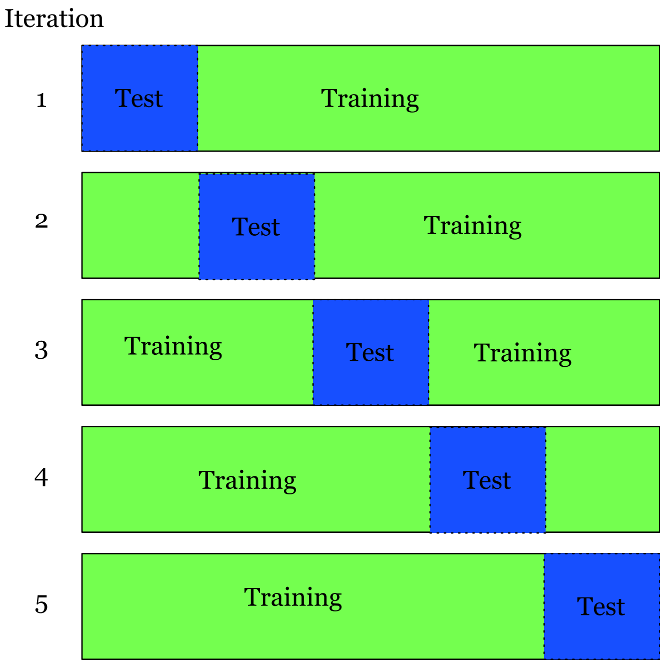
Binarized (Boolean feature) Multinomial Naïve Bayes

- Binary seems to work better than full word counts
  - This is **not** the same as Multivariate Bernoulli Naïve Bayes
    - MBNB doesn't work well for sentiment or other text tasks
- Other possibility: log(freq(*w*))

B. Pang, L. Lee, and S. Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79-86.
V. Metsis, I. Androutsopoulos, G. Paliouras. 2006. Spam Filtering with Naive Bayes – Which Naive Bayes? CEAS 2006 - Third Conference on Email and Anti-Spam.
K.-M. Schneider. 2004. On word frequency information and negative evidence in Naive Bayes text classification. ICANLP, 474-485.
JD Rennie, L Shih, J Teevan. 2003. Tackling the poor assumptions of naive bayes text classifiers. ICML 2003

交叉验证 Cross-Validation

- Break up data into N folds
- For each fold
  - Choose the fold as a temporary test set
  - Train on N-1 folds, compute performance on the test fold
- Report average performance of the N runs



Results on polarity dataset v0.9

	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	"	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

Figure 3: Average three-fold cross-validation accuracies, in percent. Boldface: best performance for a given setting (row). Recall that our baseline results ranged from 50% to 69%.

B. Pang, L. Lee, and S. Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79-86

情感分析的难点

- “This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it **can’t hold up**.”
- Well as usual Keanu Reeves is nothing special, but surprisingly, the very talented Laurence Fishbourne is **not so good** either, I was surprised.

数据集的平衡性对结果的影响

- If not balanced (common in the real world)
  - can’t use accuracies as an evaluation
  - need to use F-scores
- Severe imbalancing also can degrade classifier performance
- Two common solutions:
  1. Resampling in training
     - Random undersampling
  2. Cost-sensitive learning
     - Penalize more for misclassification of the rare thing

如何处理多个情感等级

1. Map to binary
2. Use linear or ordinal regression
   - Or specialized models like metric labeling

Bo Pang and Lillian Lee. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. ACL, 115–124

小结

- Generally modeled as classification or regression task
  - predict a binary or ordinal label
- Features:
  - Negation is important
  - Using all words (in naïve bayes) works well for some tasks
  - Finding subsets of words may help in other tasks
    - Hand-built polarity lexicons
    - Use seeds and semi-supervised learning to induce lexicons

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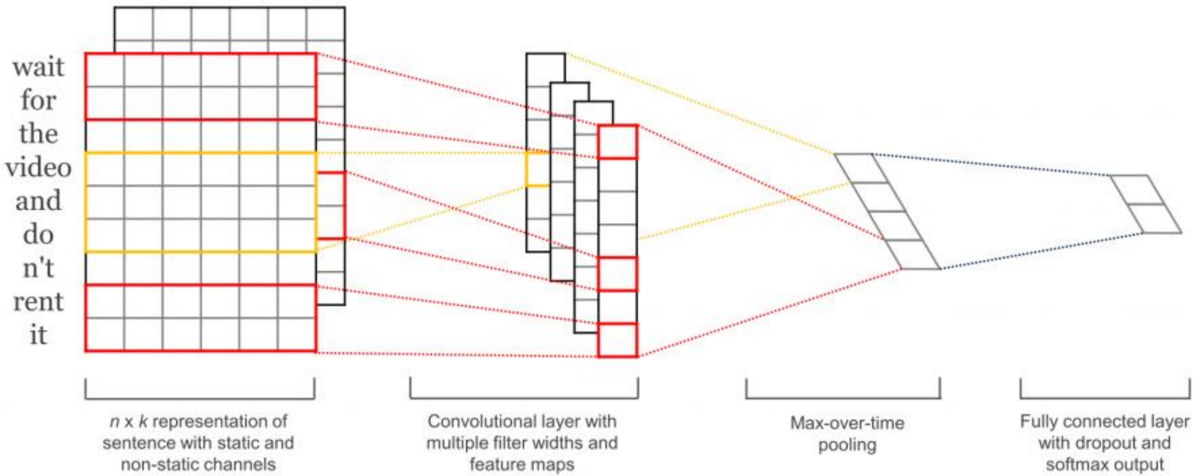
基于CNN的情感分析



参考实现：http://www.wildml.com/2015/12/implementing-a-cnn-for-text-classification-in-tensorflow/

参考论文：Kim Y. Convolutional Neural Networks for Sentence Classification. empirical methods in natural language processing, 2014: 1746-1751.

CNN模型的变体

- **CNN-rand**: baseline model where all words are randomly initialized and then modified during training.
- **CNN-static**: A model with pre-trained vectors from word2vec. All words—including the unknown ones that are randomly initialized—are kept static and only the other parameters of the model are learned.
- **CNN-non-static**: Same as above but the pretrained vectors are fine-tuned for each task.
- **CNN-multichannel**: A model with two sets of word vectors. Each set of vectors is treated as a 'channel' and each filter is applied

CNN模型的效果

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN (Socher et al., 2012)	79.0	44.4	82.9	–	–	–	–
RNTN (Socher et al., 2013)	–	45.7	85.4	–	–	–	–
DCNN (Kalchbrenner et al., 2014)	–	48.5	86.8	–	93.0	–	–
Paragraph-Vec (Le and Mikolov, 2014)	–	**48.7**	87.8	–	–	–	–
CCAE (Hermann and Blunsom, 2013)	77.8	–	–	–	–	–	87.2
Sent-Parser (Dong et al., 2014)	79.5	–	–	–	–	–	86.3
NBSVM (Wang and Manning, 2012)	79.4	–	–	93.2	–	81.8	86.3
MNB (Wang and Manning, 2012)	79.0	–	–	**93.6**	–	80.0	86.3
G-Dropout (Wang and Manning, 2013)	79.0	–	–	93.4	–	82.1	86.1
F-Dropout (Wang and Manning, 2013)	79.1	–	–	**93.6**	–	81.9	86.3
Tree-CRF (Nakagawa et al., 2010)	77.3	–	–	–	–	81.4	86.1
CRF-PR (Yang and Cardie, 2014)	–	–	–	–	–	82.7	–
SVM_S (Silva et al., 2011)	–	–	–	–	**95.0**	–	–

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方面(Aspect)级情感分析

- Important for finding aspects or attributes
  - Target of sentiment
- `The food was great but the service was awful`

方面(Aspect)级情感分析

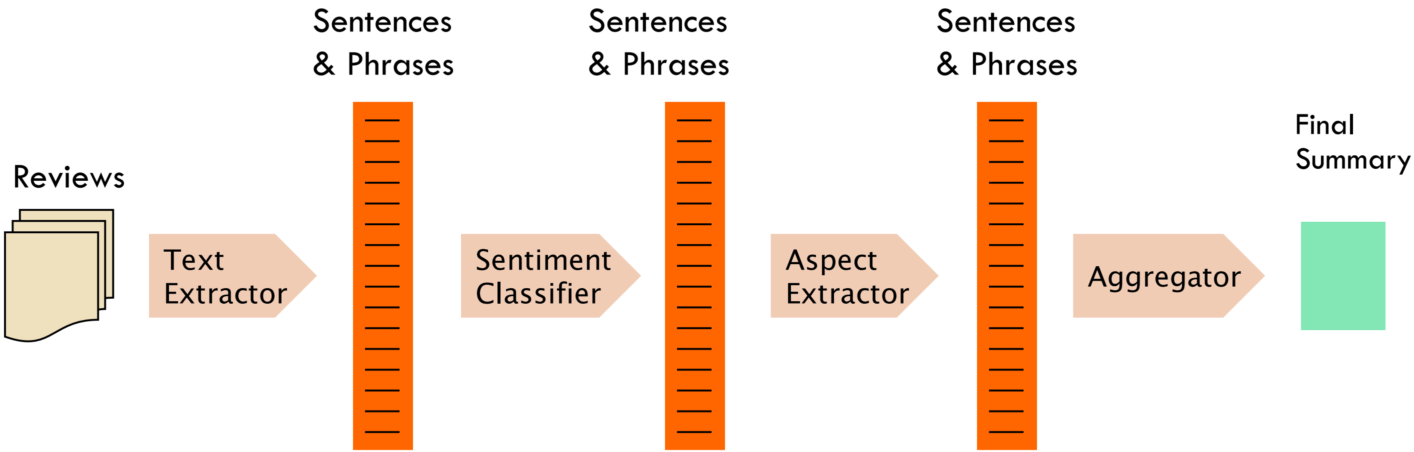
- Frequent phrases + rules
  - Find all highly frequent phrases across reviews

Casino	casino, buffet, pool, resort, beds
Children's Barber	haircut, job, experience, kids
Greek Restaurant	food, wine, service, appetizer, lamb
Department Store	selection, department, sales, shop, clothing

  - Filter by rules like "occurs right after sentiment word"
    - "…`great fish tacos`" means `fish tacos` a likely aspect

M. Hu and B. Liu. 2004. Mining and summarizing customer reviews. In Proceedings of KDD.
S. Blair-Goldensohn, K. Hannan, R. McDonald, T. Neylon, G. Reis, and J. Reynar. 2008. Building a Sentiment Summarizer for Local Service Reviews. WWW Workshop.

方面(Aspect)级情感分析—情感摘要



S. Blair-Goldensohn, K. Hannan, R. McDonald, T. Neylon, G. Reis, and J. Reynar. 2008. Building a Sentiment Summarizer for Local Service Reviews. WWW Workshop

方面(Aspect)级情感分析—情感摘要

Rooms (3/5 stars, 41 comments)

- (+) The room was clean and everything worked fine – even the water pressure ...
- (+) We went because of the free room and was pleasantly pleased ...
- (-) ...the worst hotel I had ever stayed at ...

Service (3/5 stars, 31 comments)

- (+) Upon checking out another couple was checking early due to a problem ...
- (+) Every single hotel staff member treated us great and answered every ...
- (-) The food is cold and the service gives new meaning to SLOW.

Dining (3/5 stars, 18 comments)

- (+) our favorite place to stay in biloxi. the food is great also the service ...
- (+) Offer of free buffet for joining the Play

其他情感计算相关任务

- **Emotion**:
  - Detecting annoyed callers to dialogue system
  - Detecting confused/frustrated versus confident students
- **Mood**:
  - Finding traumatized or depressed writers
- **Interpersonal stances（人际关系立场）**：
  - Detection of flirtation or friendliness in conversations
- **Personality traits**:
  - Detection of extroverts（外向型人格检测）

情感分析的发展方向

- 细粒度情感分析
- 多模态情感分析
- 对话中的情感分析
- 隐喻、幽默识别等

本章参考资料

- 斯坦福大学公开课：自然语言处理 情感分析部分
  - Dan Jurafsky
  - https://www.bilibili.com/video/BV1YW41147Up?p=33