Natural Language Processing

Sentiment analysis

The problem of sentiment analysis

Sentiment analysis or **opinion mining** is the computational study of opinions, sentiments and emotions expressed in text.

Example: “(1) *I bought an iPhone a few days ago.* (2) *It was such a nice phone.* (3) *The touch screen was really cool.* (4) *The voice quality was clear too.* (5) *Although the battery life was not long, that is ok for me.* (6) *However, my mother was mad with me as I did not tell her before I bought it.* (7) *She also thought the phone was too expensive, and wanted me to return it to the shop.* ...”

The problem of sentiment analysis

An **object** *o* is an entity which can be a product, person, event, organization, or topic. It is associated with a pair o:(T, A), where T is a hierarchy of components (or parts), sub-components etc., and A is a set of attributes of o.

Example: A particular brand of cellular phone is an **object**. It has a set of **components**, e.g. battery, screen, and also a set of **attributes**, e.g. voice quality, size, weight. The battery component also has its set of attributes, e.g. battery life, battery size.

The problem of sentiment analysis

Let an **opinionated document** be *d*, which can be a product review, a forum post or a blog that evaluates a set of objects. In the most general case, *d* consists of a sequence of sentences $d = \langle s_1, s_2, \ldots, s_m \rangle$.

An **opinion passage** on a feature *f* of an object *O* evaluated in *d* is a group of consecutive sentences in *d* that express a positive or negative opinion on *f*.

If a feature *f* appears in a sentence *s*, *f* is called an **explicit feature** in *s*. If neither *f* nor any of its synonyms appear in *s* but *f* is implied, then *f* is called an **implicit feature** in *s*.

- Explicit feature: "*The battery life of this phone is too short*";
- Implicit feature: "*This phone is too large*".

The problem of sentiment analysis

The **holder of an opinion** is the person or organization that expresses the opinion.

An **opinion** on a feature *f* is a positive or negative view, attitude, emotion or appraisal on *f* from an opinion holder.

The **orientation of an opinion** on a feature *f* indicates whether the opinion is positive, negative or neutral.

Model of an object: An object *o* is represented with a finite set of features, $F = \{f_1, \ldots, f_n\}$, which includes the object itself as a special feature. Each feature can be expressed with any one of a finite set of words or phrases $W_i = \{w_{i1}, \ldots, w_{im}\}$, which are synonyms of the feature, or indicated by any one of a finite set of feature indicators $I_i = \{i_{i1}, \ldots, i_{iq}\}$ of the feature.

The problem of sentiment analysis

Model of an opinionated document: A general opinionated document *d* contains opinions on a set of objects $\{o_1, \ldots, o_q\}$ from a set of opinion holders $\{h_1, \ldots, h_p\}$. The opinions on each object o_j are expressed on a subset F_j of features of o_j. An opinion can be any one of the following two types:

1. A **direct opinion** is a quintuple $(o_j, f_{jk}, oo_{ijkl}, h_i, t_l)$, where o_j is an object, f_{jk} is a feature of the object o_j, oo_{ijkl} is the orientation or polarity of the opinion on feature f_{jk} of object o_j, h_i is the opinion holder and t_l is the time when the opinion is expressed by h_i.
2. A **comparative opinion** expresses a relation of similarities or differences between two or more objects, and/or object preferences of the opinion holder based on some of the shared features of the objects.

The problem of sentiment analysis

Direct opinions:

1. opinions are directly expresses on an object or features of the object, e.g., "*The voice quality of this phone is great.*";
2. opinions on an object are expressed based on its effect on some other objects, e.g., "*After taking this drug, my left knee felt great*".

Objective of mining direct opinions: Given an opinionated document *d*,

1. discover all opinion quintuples (o_j, f_{jk}, oo_{ijkl}, h_i, t_l) in *d*, and
2. identify all the synonyms (W_{jk}) and feature indicators I_{jk} of each feature f_{jk} in *d*.

The problem of sentiment analysis

Example: “(1) *This past Saturday, I bought a Nokia phone and my girlfriend bought a Motorola phone.* (2) *We called each other when we got home.* (3) *The voice on my phone was not so clear, worse than my previous phone.* (4) *The camera was good.* (5) *My girlfriend was quite happy with her phone.* (6) *I wanted a phone with good voice quality.* (7) *So my purchase was a real disappointment.* (8) *I returned the phone yesterday.*”

An **objective sentence** expresses some factual information about the world (№ 1, 2, 8), while a **subjective sentence** expresses some personal feelings or beliefs.

The problem of sentiment analysis

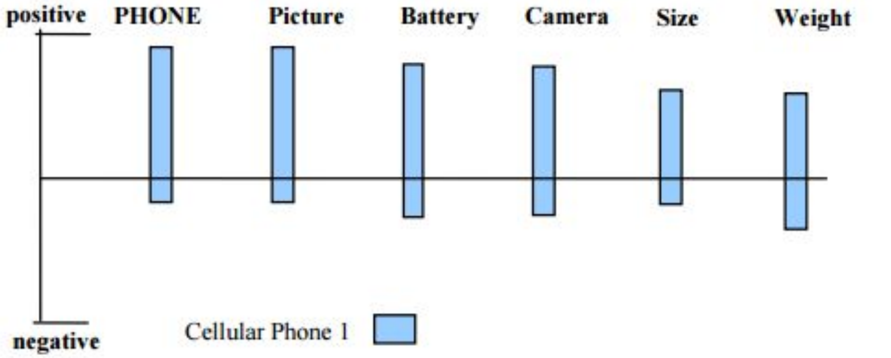
An **explicit opinion** on feature *f* is an opinion explicitly expressed on *f* in a subjective sentence. An **implicit opinion** on feature *f* is an opinion on *f* implied in an objective sentence.

Explicit positive opinion: "*The voice quality of this phone is amazing.*"

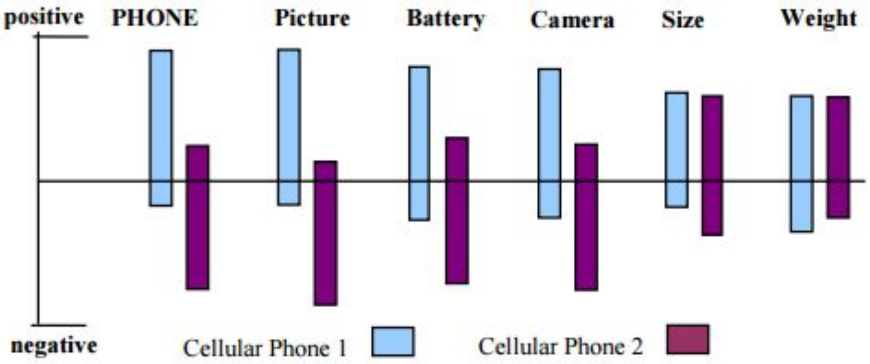
Implicit negative opinion: "*The earphone broke in two days.*"

An **opinionated sentence** is a sentence that expresses explicit or implicit positive or negative opinions. It can be a subjective or objective sentence.

The problem of sentiment analysis



(A) Visualization of feature-based summary of opinions on a cellular phone



(B) Visual opinion comparison of two cellular phones

The problem of sentiment analysis

A simple way to use the results is to produce a **feature-based summary** of opinions on an object or multiple competing objects.

Examples of summary types:

- **Feature buzz summary**: shows the relative frequency of feature mentions. It can tell a company what their customers really care about;
- **Object buzz summary**: shows the frequency of mentions of different competing products. This is useful because it tells the popularity of different products or brands in the market place;
- **Trend tracking**: If the time dimension is added to the above summaries, we get their trend reports. These reports can be extremely helpful in practice because the user always wants to know how things change over time.

Document-Level Sentiment Classification

Task: Given an opinionated document *d* which comments on an object *o*, determine the orientation *oo* of the opinion expressed on *o*, i.e., discover the opinion orientation *oo* on feature *f* in the quintuple (*o*, *f*, *so*, *h*, *t*), where *f* = *o* and *h*, *t*, *o* are assumed to be known or irrelevant.

Assumption: The opinionated document *d* (e.g., a product review) expresses opinions on a single object *o* and the opinions are from a single opinion holder *h*.

Classification Based on Supervised Learning

Features:

- Terms and their frequency;
- Part of speech tags;
- Opinion words and phrases;
- Syntactic dependenies;
- Negation.

Classification Based on Unsupervised Learning

Step 1: extracting phrases containing adjectives or adverbs.

Table 1. Patterns of POS tags for extracting two-word phrases

	First word	Second word	Third word (Not Extracted)
1.	JJ	NN or NNS	anything
2.	RB, RBR, or RBS	JJ	not NN nor NNS
3.	JJ	JJ	not NN nor NNS
4.	NN or NNS	JJ	not NN nor NNS
5.	RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

In the sentence, "*This camera produces beautiful pictures*", "*beautiful pictures*" will be extracted as it satisfies the first pattern.

Classification Based on Unsupervised Learning

Step 2: estimation of the orientation of the extracted phrases using the **pointwise mutual information** (PMI) measure:

$$PMI(term_1, term_2) = \log_2\left(\frac{\Pr(term_1 \wedge term_2)}{\Pr(term_1)\Pr(term_2)}\right).$$

The opinion orientation (*oo*) of a phrase is computed based on its association with the positive reference word “excellent” and its association with the negative reference word “poor”:

$$oo(phrase) = PMI(phrase, \text{“}excellent\text{”}) - PMI(phrase, \text{“}poor\text{”}).$$

$$oo(phrase) = \log_2\left(\frac{hits(\text{phrase } NEAR \text{ "excellent"})hits(\text{"poor"})}{hits(\text{phrase } NEAR \text{ "poor"})hits(\text{"excellent"})}\right).$$

Hits is the number of relevant documents to the search query.

Classification Based on Unsupervised Learning

Step 3: Given a review, the algorithm computes the average *oo* of all phrases in the review, and classifies the review as recommended if the average *oo* is positive, not recommended otherwise.

Sentence-Level Subjectivity

Task: Given a sentence *s*, two sub-tasks are performed:

1. Subjectivity classification: Determine whether *s* is a subjective sentence or an objective sentence;

2. Sentence-level sentiment classification: If *s* is subjective, determine whether it expresses a positive or negative opinion.

Assumption of sentence-level sentiment classification: The sentence expresses a single opinion from a single opinion holder.

Opinion Lexicon Generation

Positive opinion words (*beautiful*, *wonderful*, *good*, and *amazing*) are used to express desired states while **negative opinion words** (*bad*, *poor*, and *terrible*) are used to express undesired states. Apart from individual words, there are also **opinion phrases and idioms**, e.g., *cost someone an arm and a leg*. Collectively, they are called the **opinion lexicon**.

Opinion words types:

- the base type;
- the comparative type, e.g. *better*, *worse*, *best*, *worst*, etc.

Opinion Lexicon Generation

Dictionary-based approach: first collect a small set of opinion words manually with known orientations, and then to grow this set by searching in the dictionary (e.g. WordNet) for their synonyms and antonyms. The newly found words are added to the seed list. The next iteration starts. The iterative process stops when no more new words are found.

Corpus-based approach and sentiment consistency: The methods in the corpus-based approach rely on syntactic or co-occurrence patterns and also a seed list of opinion words to find other opinion words in a large corpus.

Feature-Based Sentiment Analysis

1. Identify object features that have been commented on. For instance, in the sentence, “*The picture quality of this camera is amazing*,” the object feature is “*picture quality*”;
2. Determine whether the opinions on the features are positive, negative or neutral. In the above sentence, the opinion on the feature “*picture quality*” is positive.

Feature Extraction

Format 1 − Pros, cons and the detailed review: The reviewer is asked to describe Pros and Cons separately and also write a detailed/full review.

Format 2 − Free format: The reviewer can write freely, i.e., no separation of Pros and Cons.

My SLR is on the shelf

by camerafun4. Aug 09 ‘04

Pros: Great photos, easy to use, very small
Cons: Battery usage; included memory is stingy.

I had never used a digital camera prior to purchasing this Canon A70. I have always used a SLR ... **Read the full review**

GREAT Camera., Jun 3, 2004

Reviewer: **jprice174** from Atlanta, Ga.

I did a lot of research last year before I bought this camera... It kinda hurt to leave behind my beloved nikon 35mm SLR, but I was going to Italy, and I needed something smaller, and digital.

The pictures coming out of this camera are amazing. The 'auto' feature takes great pictures most of the time. And with digital, you're not wasting film if the picture doesn't come out. ...

Feature Extraction from Pros and Cons of Format 1

Pros can be separated into three segments:

- great photos ⟨photo⟩
- easy to use ⟨use⟩
- very small ⟨small⟩ ⇒ ⟨size⟩

Cons can be separated into two segments:

- battery usage ⟨battery⟩
- included memory is stingy ⟨memory⟩

Feature Extraction from Pros and Cons of Format 1

The rules are called label sequential rules (LSR), which are generated from sequential patterns in data mining. A **label sequential rule** (LSR) is of the following form, $X \rightarrow Y$, where Y is a sequence and X is a sequence produced from Y by replacing some of its items with wildcards. A wildcard, denoted by a '*', can match any item.

Feature Extraction from Pros and Cons of Format 1

For example, the sentence segment, “*Included memory is stingy*”, is turned into the sequence 〈{included, VB}{memory, NN}{is, VB}{stingy, JJ}〉.

After labeling, it becomes: 〈{included, VB}{$feature, NN}{is, VB}{stingy, JJ}〉.

All the resulting sequences are then used to mine LSRs.

An example rule is: 〈{easy, JJ }{to}{*, VB}〉 → 〈{easy, JJ }{to}{$feature, VB}〉 confidence = 90%,

where the confidence is the conditional probability, Pr(Y | X), which measures the accuracy of the rule.

Feature Extraction from Reviews of Format 2

- Finding frequent nouns and noun phrases;
- Finding infrequent features by making use of opinion words.

Example: "*picture*" is found to be a frequent feature, and we have the sentence, "*The pictures are absolutely amazing.*" If we know that "*amazing*" is a positive opinion word, then "*software*" can also be extracted as a feature from the following sentence, "*The software is amazing.*" because the two sentences follow the same pattern and "*software*" in the sentence is also a noun.

Opinion Orientation Identification

The lexicon-based approach basically uses opinion words and phrases in a sentence to determine the orientation of the opinion. Apart from the opinion lexicon, negations and but-clauses in a sentence are also crucial and need to be handled. The approach works as follows:

1. Identifying opinion words and phrases: "*The picture quality of this camera is not great*[**+1**], *but the battery life is long*[**0**]" ;
2. Handling negations: "*The picture quality of this camera is not great*[**-1**], *but the battery life is long*[**0**]";
3. But-clauses: "*The picture quality of this camera is not great*[**-1**], *but the battery life is long*[**+1**]";
4. Aggregating opinions:

$$score(f_i, s) = \sum_{op_j \in s} \frac{op_j.so}{d(op_j, f_i)},$$

Sentiment Analysis of Comparative Sentences

Types of comparative relations:

1. Non-equal gradable comparisons: Relations of the type greater or less than that express an ordering of some objects with regard to some of their features, e.g., "*The Intel chip is faster than that of AMD*";
2. Equative comparisons: Relations of the type equal to that state two objects are equal with respect to some of their features, e.g., "*The picture quality of camera X is as good as that of camera Y*";
3. Superlative comparisons: Relations of the type greater or less than all others that rank one object over all others, e.g., "*The Intel chip is the fastest*";
4. Non-gradable comparisons: Relations that compare features of two or more objects, but do not grade them.

Sentiment Analysis of Comparative Sentences

Non-gradable comparisons:

- Object *A* is similar to or different from object *B* with regard to some features, e.g., "*Coke tastes differently from Pepsi*";
- Object *A* has feature f_1, and object *B* has feature f_2 (f_1 and f_2 are usually substitutable), e.g., "*desktop PCs use external speakers but laptops use internal speakers*";
- Object *A* has feature *f*, but object *B* does not have, e.g., "*Cell phone X has an earphone, but cell phone Yoes not have*".

Sentiment Analysis of Comparative Sentences

Given an opinionated document *d*, comparison mining consists of two tasks:

1. Identify comparative sentences in *d*, and classify the identified comparative sentences into different types or classes;
2. Extract comparative opinions from the identified sentences. A comparative opinion in a comparative sentence is expressed with: (O_1, O_2, F, po, h, t), where O_1 and O_2 are the object sets being compared based on their shared features F (objects in O_1 appear before objects in O_2 in the sentence), po is the preferred object set of the opinion holder h, and t is the time when the comparative opinion is expressed.

Sentiment Analysis of Comparative Sentences

Example: Consider the comparative sentence "*Canon's optics is better than those of Sony and Nikon.*" written by John on May 1, 2009.

The extracted comparative opinion is: ({*Canon*}, {*Sony*, *Nikon*}, {*optics*}, preferred:{*Canon*}, *John*, *May-1-2009*).

The object set O_1 is {*Canon*}, the object set O_2 is {*Sony*, *Nikon*}, their shared feature set *F* being compared is {*optics*}, the preferred object set is {*Canon*}, the opinion holder *h* is *John* and the time *t* when this comparative opinion was written is *May-1-2009.*

Text String Element	Automated	Manual/Human
Ability to detect sarcasm?	✗	✓
Emoticon analysis?	✗	✓
Slang and abbreviation analysis?	✗	✓
Time Efficiency	High	Low to Medium
Accuracy	Low to Medium	High
Contextual Analysis	✗	✓

Semantic thesaurus

SentiWordNet: http://sentiwordnet.isti.cnr.it/ ;

SenticNet: http://sentic.net/ ;

WordNet-Affect: http://wndomains.fbk.eu/wnaffect.html .

Sentiment Analysis

https://nlp.stanford.edu/sentiment/

This deep learning model builds up a representation of whole sentences based on the sentence structure. It computes the sentiment based on how words compose the meaning of longer phrases.

Stanford Sentiment Bank

The original dataset includes 10,662 sentences, half of which were considered positive and the other half negative.

Text prepocessing: normalizing, lowercasing, deleting HTML tags and not-English sentences.

The Stanford Parser is used to parses all 10,662 sentences. In approximately 1,100 cases it splits the snippet into multiple sentences. They then used Amazon Mechanical Turk to label the resulting 215,154 phrases.

Stanford Sentiment Bank

Figure 3: The labeling interface. Random phrases were shown and annotators had a slider for selecting the sentiment and its degree.

Stanford Sentiment Bank

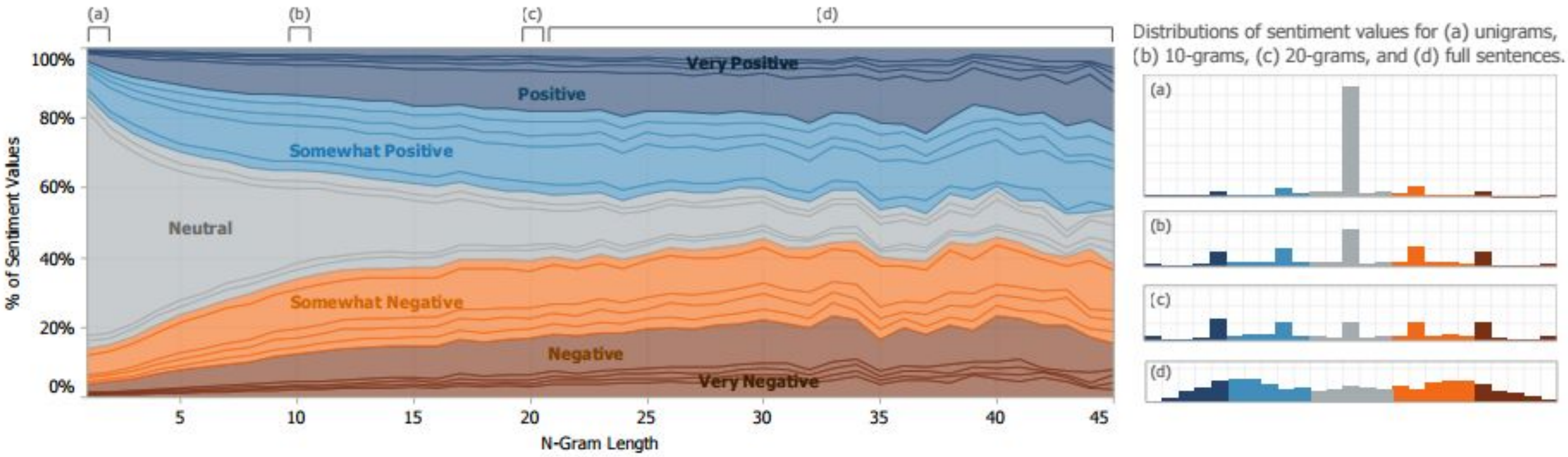


Figure 2: Normalized histogram of sentiment annotations at each n-gram length. Many shorter n-grams are neutral; longer phrases are well distributed. Few annotators used slider positions between ticks or the extreme values. Hence the two strongest labels and intermediate tick positions are merged into 5 classes.

Recursive Neural Networks

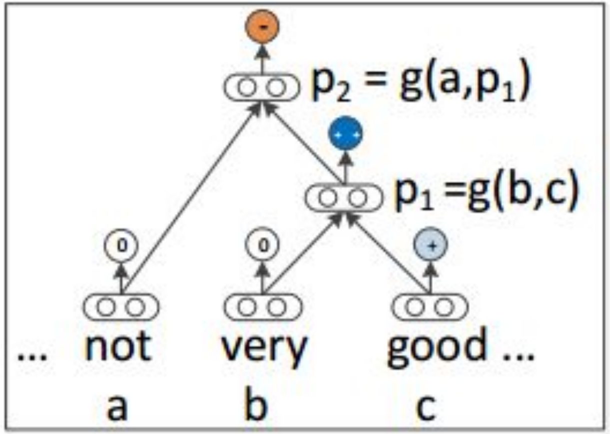


Figure 4: Approach of Recursive Neural Network models for sentiment: Compute parent vectors in a bottom up fashion using a compositionality function g and use node vectors as features for a classifier at that node. This function varies for the different models.

Results

Model	Fine-grained		Positive/Negative	
	All	Root	All	Root
NB	67.2	41.0	82.6	81.8
SVM	64.3	40.7	84.6	79.4
BiNB	71.0	41.9	82.7	83.1
VecAvg	73.3	32.7	85.1	80.1
RNN	79.0	43.2	86.1	82.4
MV-RNN	78.7	44.4	86.8	82.9
RNTN	**80.7**	**45.7**	**87.6**	**85.4**

Table 1: Accuracy for fine grained (5-class) and binary predictions at the sentence level (root) and for all nodes.

Contrastive Conjunction

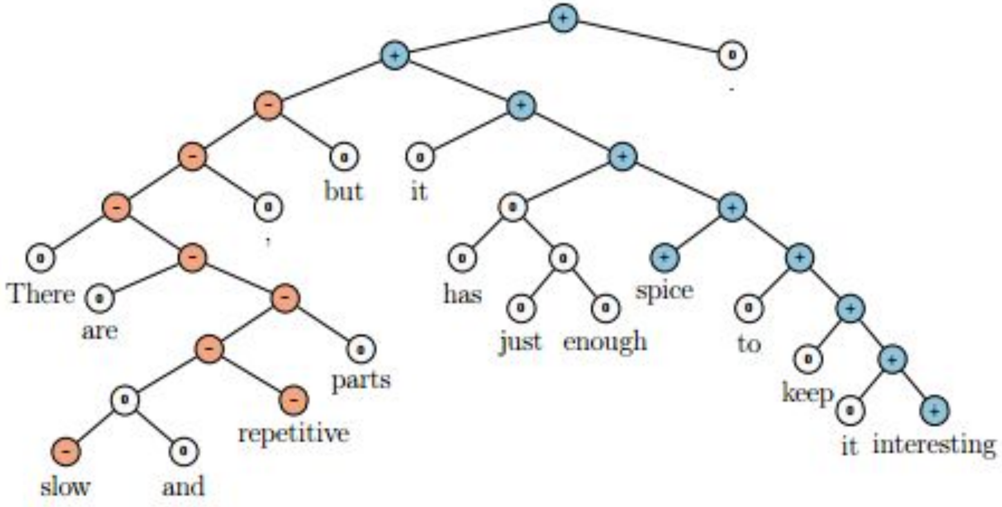
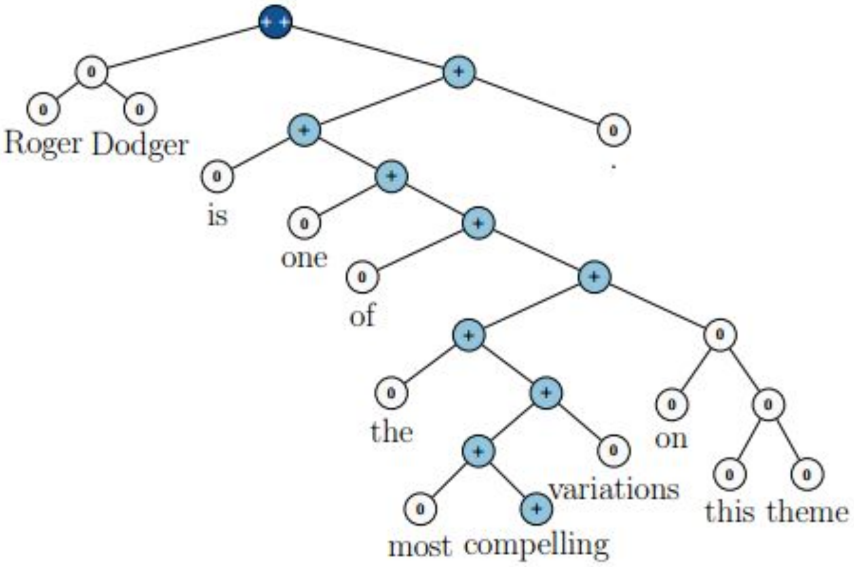
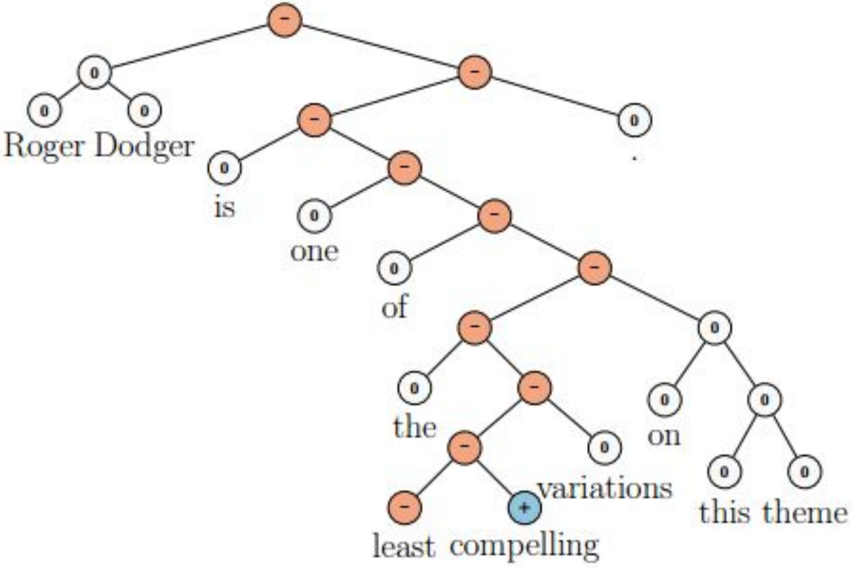


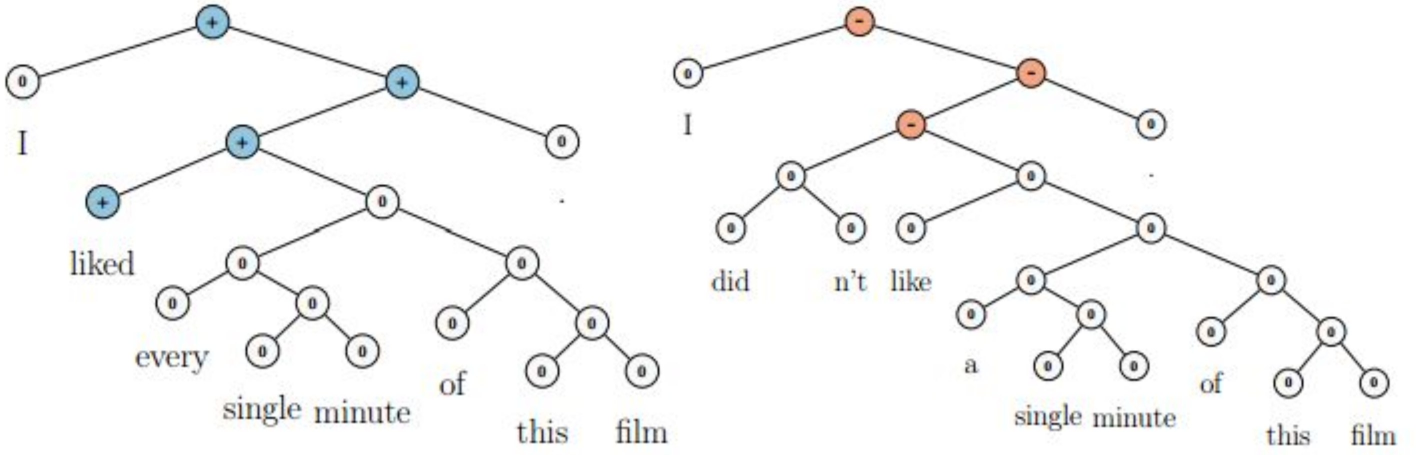
Figure 7: Example of correct prediction for contrastive conjunction X *but* Y.

Negating Positive Sentences

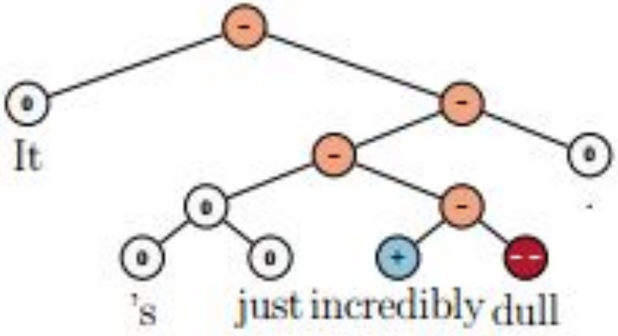


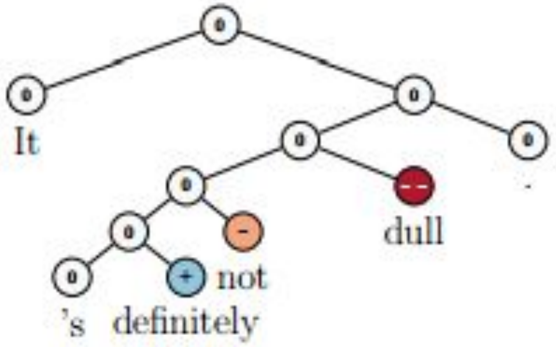


Negating Positive Sentences



Negating Negative Sentences





Negation Detection

Model	Accuracy	
	Negated Positive	Negated Negative
biNB	19.0	27.3
RNN	33.3	45.5
MV-RNN	52.4	54.6
RNTN	**71.4**	**81.8**

Table 2: Accuracy of negation detection. Negated positive is measured as correct sentiment inversions. Negated negative is measured as increases in positive activations.

n	Most positive n-grams	Most negative n-grams
1	engaging; best; powerful; love; beautiful	bad; dull; boring; fails; worst; stupid; painfully
2	excellent performances; A masterpiece; masterful film; wonderful movie; marvelous performances	worst movie; very bad; shapeless mess; worst thing; instantly forgettable; complete failure
3	an amazing performance; wonderful all-ages triumph; a wonderful movie; most visually stunning	for worst movie; A lousy movie; a complete failure; most painfully marginal; very bad sign
5	nicely acted and beautifully shot; gorgeous imagery, effective performances; the best of the year; a terrific American sports movie; refreshingly honest and ultimately touching	silliest and most incoherent movie; completely crass and forgettable movie; just another bad movie. A cumbersome and cliche-ridden movie; a humorless, disjointed mess
8	one of the best films of the year; A love for films shines through each frame; created a masterful piece of artistry right here; A masterful film from a master filmmaker,	A trashy, exploitative, thoroughly unpleasant experience ; this sloppy drama is an empty vessel.; quickly drags on becoming boring and predictable.; be the worst special-effects creation of the year

Table 3: Examples of n-grams for which the RNTN predicted the most positive and most negative responses.

Opinion Mining with Deep RNN

http://www.cs.cornell.edu/~oirsoy/files/emnlp14drnt.pdf

Authors focus on the detection of opinion expressions — both direct subjective expressions (DSEs) and expressive subjective expressions (ESEs). **DSEs** consist of explicit mentions of private states or speech events expressing private states; and **ESEs** consist of expressions that indicate sentiment, emotion, etc., without explicitly conveying them.

The	committee	,	as	usual	,	has
O	O	O	B_ESE	I_ESE	O	B_DSE
refused	to	make	any	statements	.	
I_DSE	I_DSE	I_DSE	I_DSE	I_DSE	O	

Opinion Mining with Deep RNN

Methods:

- Conditional Random Fields (CRF);
- Recurrent Neural Networks (RNN);
- Bidirectional RNNs;
- Deep Recurrent Networks

Hypothesis

The authors expected that the deep RNNs would show the most improvement over shallow RNNS for ESEs — phrases that implicitly convey subjectivity. Existing research has shown that these are harder to identify than direct expressions of subjectivity (DSEs): they are variable in length and involve terms that, in many (or most) contexts, are neutral with respect to sentiment and subjectivity. As a result, models that do a better job interpreting the context should be better at disambiguating subjective vs. non- subjective uses of phrases involving common words (e.g. "*as usual*", "*in fact*").

Experiments: Data

Authors use the MPQA 1.2 corpus (535 news articles, 11,111 sentences) that is manually annotated with both DSEs and ESEs at the phrase level. 135 documents were separated as a development set and employ 10-fold CV over the remaining 400 documents. The development set is used during cross validation to do model selection.

Experiments: Evaluation Metrics

The authors use precision, recall and F-measure for performance evaluation. Since the boundaries of expressions are hard to define even for human annotators authors use two soft notions of the measures: Binary Overlap counts every overlapping match between a predicted and true expression as correct, and Proportional Overlap imparts a partial correctness, proportional to the overlapping amount, to each match.

Results: Bidirectional vs. Unidirectional

	DSE		ESE	
	Prop.	Bin.	Prop.	Bin.
Unidirectional	60.35	68.31	51.51	63.65
Bidirectional	63.83	69.62	54.22	65.44

F1 scores

Results: Adding Depth

Layers	|h|	Precision Prop.	Precision Bin.	Recall Prop.	Recall Bin.	F1 Prop	F1 Bin.
Shallow	36	62.24	65.90	65.63*	73.89*	63.83	69.62
Deep 2	29	63.85*	67.23*	65.70*	**74.23***	64.70*	70.52*
Deep 3	25	63.53*	67.67*	65.95*	73.87*	64.57*	70.55*
Deep 4	22	**64.19***	**68.05***	**66.01***	73.76*	**64.96***	**70.69***
Deep 5	21	60.65	61.67	56.83	69.01	58.60	65.06
Shallow	200	62.78	66.28	65.66*	74.00*	64.09	69.85
Deep 2	125	62.92*	66.71*	66.45*	**74.70***	64.47	70.36
Deep 3	100	**65.56***	**69.12***	**66.73***	74.69*	**66.01***	**71.72***
Deep 4	86	61.76	65.64	63.52	72.88*	62.56	69.01
Deep 5	77	61.64	64.90	62.37	72.10	61.93	68.25

Table 2: Experimental evaluation of RNNs for DSE extraction

Layers	|h|	Precision Prop.	Precision Bin.	Recall Prop.	Recall Bin.	F1 Prop	F1 Bin.
Shallow	36	51.34	59.54	57.60	72.89*	54.22	65.44
Deep 2	29	51.13	59.94	**61.20***	**75.37***	**55.63***	**66.64***
Deep 3	25	**53.14***	**61.46***	58.01	72.50	55.40*	66.36*
Deep 4	22	51.48	60.59*	59.25*	73.22	54.94	66.15*
Deep 5	21	49.67	58.42	48.98	65.36	49.25	61.61
Shallow	200	**52.20***	60.42*	58.11	72.64	54.75	65.75
Deep 2	125	51.75*	60.75*	60.69*	74.39*	55.77*	66.79*
Deep 3	100	52.04*	**60.50***	**61.71***	**76.02***	**56.26***	**67.18***
Deep 4	86	50.62*	58.41*	53.55	69.99	51.98	63.60
Deep 5	77	49.90*	57.82	52.37	69.13	51.01	62.89

Table 3: Experimental evaluation of RNNs for ESE extraction

Results: Comparison with Baselines

	Model		Precision		Recall		F1	
			Prop.	Bin.	Prop.	Bin.	Prop	Bin.
DSE	CRF		74.96*	82.28*	46.98	52.99	57.74	64.45
	semiCRF		61.67	69.41	**67.22***	73.08*	64.27	71.15*
	CRF	+vec	**74.97***	**82.43***	49.47	55.67	59.59	66.44
	semiCRF	+vec	66.00	71.98	60.96	68.13	63.30	69.91
	Deep RNN	3 100	65.56	69.12	66.73*	**74.69***	**66.01***	**71.72***
ESE	CRF		56.08	68.36	42.26	51.84	48.10	58.85
	semiCRF		45.64	69.06	58.05	64.15	50.95	66.37*
	CRF	+vec	**57.15***	69.84*	44.67	54.38	50.01	61.01
	semiCRF	+vec	53.76	**70.82***	52.72	61.59	53.10	65.73
	Deep RNN	3 100	52.04	60.50	**61.71***	**76.02***	**56.26***	**67.18***

Table 4: Comparison of Deep RNNs to state-of-the-art (semi)CRF baselines for DSE and ESE detection

Examples of Output

(1)

	The situation obviously remains fluid from hour to hour but it [seems to be] [going in the right direction]
deepRNN	The situation [obviously] remains fluid from hour to hour but it [seems to be going in the right] direction
Shallow	The situation [obviously] remains fluid from hour to hour but it [seems to be going in] the right direction
semiCRF	The situation [obviously remains fluid from hour to hour but it seems to be going in the right direction]

(2)

	have always said this is a multi-faceted campaign [but equally] we have also said any future military action [would have to be based on evidence] , ...
deepRNN	have always said this is a multi-faceted campaign but [equally we] have also said any future military action [would have to be based on evidence] , ...
Shallow	have always said this is a multi-faceted [campaign but equally we] have also said any future military action would have to be based on evidence , ...
semiCRF	have always said this is a multi-faceted campaign but equally we have also said any future military action would have to be based on evidence , ...

(3)

	Ruud Lubbers , the United Nations Commissioner for Refugees , said Afghanistan was [not yet] secure for aid agencies to operate in and " [not enough] " food had been taken into the country .
deepRNN	Ruud Lubbers , the United Nations Commissioner for Refugees , said Afghanistan was [not yet] secure for aid agencies to operate in and " [not enough] " food had been taken into the country .
Shallow	Ruud Lubbers , the United Nations Commissioner for Refugees , said Afghanistan was [not yet] secure for aid agencies to operate in and " [not enough] " food had been taken into the country .
semiCRF	Ruud Lubbers , the United Nations Commissioner for Refugees , said Afghanistan was not yet secure for aid agencies to operate in and " not enough " food had been taken into the country .

Unsupervised Sentiment Neuron

https://blog.openai.com/unsupervised-sentiment-neuron/

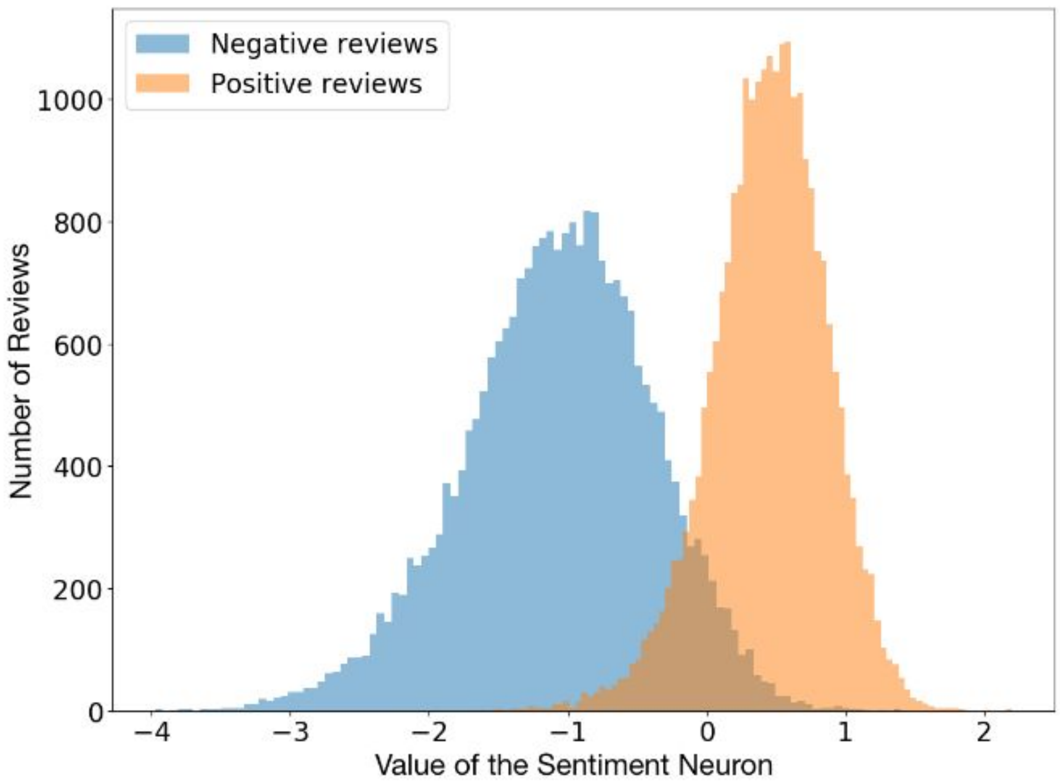
Unsupervised system which learns an excellent representation of sentiment, despite being trained only to predict the next character in the text of Amazon reviews.

Unsupervised Sentiment Neuron: Methodology

Authors first trained a LSTM with 4,096 units on a corpus of 82 million Amazon reviews to predict the next character in a chunk of text.

These 4,096 units (which are just a vector of floats) can be regarded as a feature vector representing the string read by the model. After training the LSTM, they turned the model into a sentiment classifier by taking a linear combination of these units, learning the weights of the combination via the available supervised data.

Sentiment Neuron



Example

This is one of Crichton's best books. The characters of Karen Ross, Peter Elliot, Munro, and Amy are beautifully developed and their interactions are exciting, complex, and fast-paced throughout this impressive novel. And about 99.8 percent of that got lost in the film. Seriously, the screenplay AND the directing were horrendous and clearly done by people who could not fathom what was good about the novel. I can't fault the actors because frankly, they never had a chance to make this turkey live up to Crichton's original work. I know good novels, especially those with a science fiction edge, are hard to bring to the screen in a way that lives up to the original. But this may be the absolute worst disparity in quality between novel and screen adaptation ever. The book is really, really good. The movie is just dreadful.

Thank you for your attention!