



# Lecture 12: Sentiment Analysis

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# AGENDA

01 Overview

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02 Architecture

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03 Lexicon-based Approach

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04 Machine Learning-based Approach

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# Definition

Feldman (2013)

- What is Sentiment Analysis?

✓ Computational study of opinions, sentiments, evaluations, attitudes, appraisal, affects, views, emotions, subjectivity, etc., expressed in **text**.

- Text: Reviews, blogs, discussions, news, comments, feedback,...

✓ Sentiment Analysis is sometimes called **Opinion Mining**

# Backgrounds

Feldman (2013)

- Typical Usage of Sentiment Analysis

- ✓ Extract from text how people feel about different products
- ✓ Sentiment analysis can be tricky
  - Honda Accords and Toyota Camrys are nice sedans
  - Honda Accords and Toyota Camrys are nice sedans, but hardly the best car on the road



# Backgrounds

Feldman (2013)

- Opinions are widely stated

- ✓ Organization's internal data

- Customer feedback from emails, call centers, etc.

- ✓ News and reports

- Opinions in news articles and commentaries

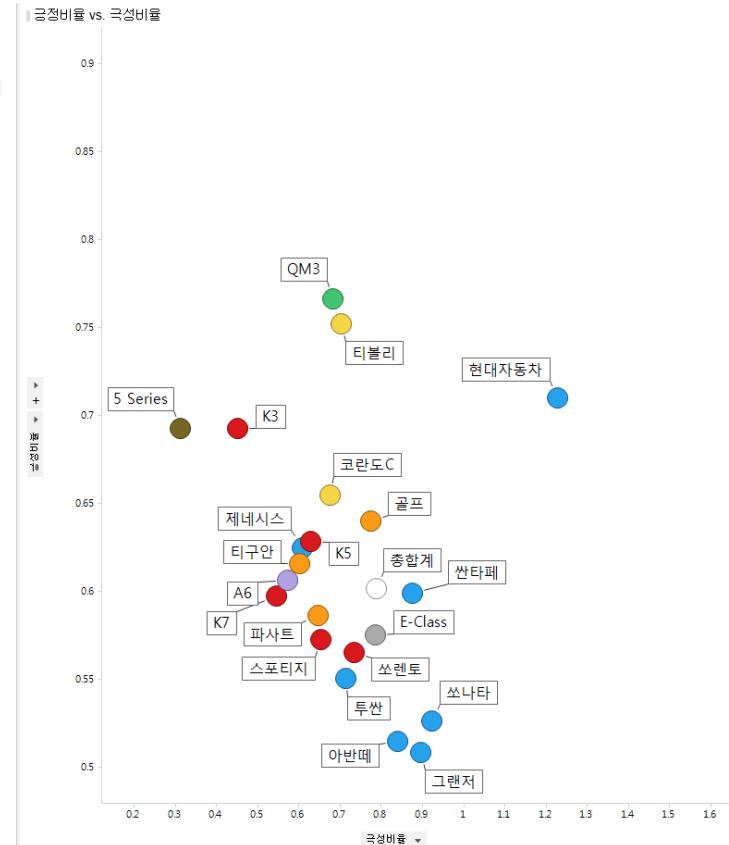
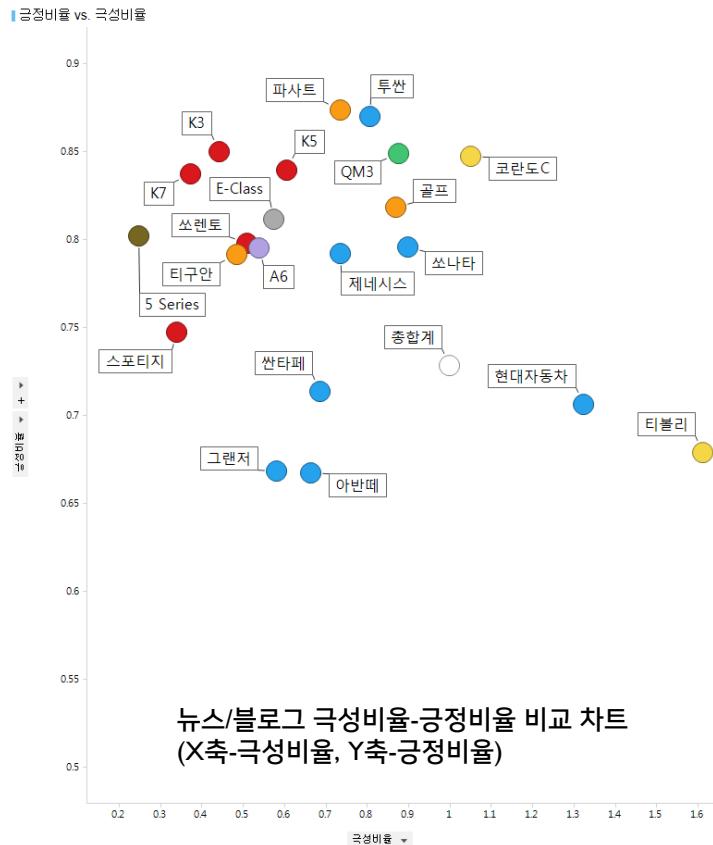
- ✓ Word-of-mouth on the web

- Personal experiences and opinions about anything in reviews, forums, blogs, Twitter, micro-blogs, etc.
    - Comments about articles, issues, topics, reviews, etc.
    - Posting at social networking sites (Facebook, Instagram, etc.)

# Applications

- Business and organizations

- ✓ Benchmark products and services; market intelligence
  - Business spend a huge amount of money to find customer opinions using consultants, surveys and focus groups, etc.



# Applications

## • Individuals

- ✓ Make decisions to purchase products or to use services
- ✓ Find public opinions about political candidates and issues



주요정보 배우/제작진 | 포토 | 동영상 | 평점 | 리뷰 | 명대사/연관영화

### 줄거리

일제강점기, 일본에서는 조선의 인종의식을 막고 그들의 지배력을 과시하기 위해 전조선자전차대회를 개최한다.

한국인 최고의 선수들을 계시고 조선인 최초로 우승을 차지한 엄복동의 등장으로 일본의 계략은 실패로 돌아가고, 계속되는 무파행진으로 '민족 영웅'으로 떠오른 그의 존재에 조선 전역은 들끓기 시작한다.

때맞춰 애국단의 활약까지 거세지자 위기감을 느낀 일본은 엄복동의 우승을 막고 조선인들의 사기를 끊기 위해 최후의 자전차 대회를 개최하는데...

일제강점기, 그 어느 때보다 드거웠던 한일전이 시작된다!

[제작노트 보기](#)

배우/제작진 [더보기 >](#)

김유성  
김득  
비  
주연 | 엄복동 역  
강소라  
주연 | 김형신 역  
이병수  
주연 | 황재호 역  
고창석  
조연 | 안도민 역  
김희원  
조연 | 사카모토 역

140자 평 | 총7,042건

▶ 호감순 ▶ 최신순 ▶ 평점 높은 순 ▶ 평점 낮은 순

관감객 평점면 보기 [?]

★★★★★ 1 골 있으면 자동차왕곽한구 나올 기세네  
초코파이(andy\*\*\*\*) | 2019.02.27 11:06 신고

[공감](#) 6881 [비공감](#) 493

★★★★★ 1 배우 정지훈... 히트작 구경한 지 언제나... 이 영화 망하고 나면 그나마도 못 나오겠네 집에서 태희 누나한테 잘 해주고 좋은 데 많이 늘려 다녀. 향복이 최고다^^ 모아둔 든 많잖아.  
13도(mak4\*\*\*\*) | 2019.02.27 09:20 신고

[공감](#) 3460 [비공감](#) 526

★★★★★ 1 이젠 관객들 뜻값도 훔쳐가네  
블랙이(the\_e\*\*\*\*) | 2019.02.27 09:04 신고

[공감](#) 3318 [비공감](#) 413

★★★★★ 1 전차왕 계엄폭동 ㅋㅋㅋ  
알캡서(kick\*\*\*\*) | 2019.02.27 11:01 신고

[공감](#) 3158 [비공감](#) 465

★★★★★ 2 제발 반일감정을 이용한 국뽕영화를 그만만드셈  
040614 대구중 박재호(wjse\*\*\*\*) | 2019.02.27 09:55 신고

[공감](#) 2748 [비공감](#) 469

★★★★★ 1 이런영화에 100억을 투자를 한거라구??정지훈 연기 왜이렇구 못하나?? 술먹고 인스타할 시간에, 연기공부좀 해라!! 술주정으로 인스타 하지 말구그리고 주식먹튀한거 사과하고 배우활동 하길뻔뻔하다 참.. 쭈쭈  
tow\*\*\*\* | 2019.02.27 09:57 신고

[공감](#) 2545 [비공감](#) 424

★★★★★ 1 리얼,악녀,염력,인랑,돌괴,창궐,엄복동  
TT(seun\*\*\*\*) | 2019.02.27 09:12 신고

[공감](#) 2443 [비공감](#) 393

# Applications

- Ad placement
  - ✓ Place an ad if one praises a product
  - ✓ Place an ad from a competitor if one criticizes a product

Guest

## Why sentiment analysis is the future of ad optimization

PETER YARED MARCH 20, 2011 6:21 PM

TAGS: KLOUT, PEERINDEX



[Peter Yared is the vice president of marketing at Klout, which he acquired Transpond, a social media measurement product, in 2010.]

Sentiment analysis is a hot topic right now. The promise of helping brands understand what consumers are thinking and saying about their products is compelling, including early contender Klout, BuzzLogic, and my own company, PeerIndex.

Measurement products are becoming pervasive, and while consumer sentiment is important, what's more important is revenue.



First Workshop  
on

Internet Advertising Using Sentiment Analysis (AdSent 2013)  
with

IEEE International Conference on Data Mining series (ICDM), December 7, Dallas, Texas, USA

# Applications

- Opinion Retrieval

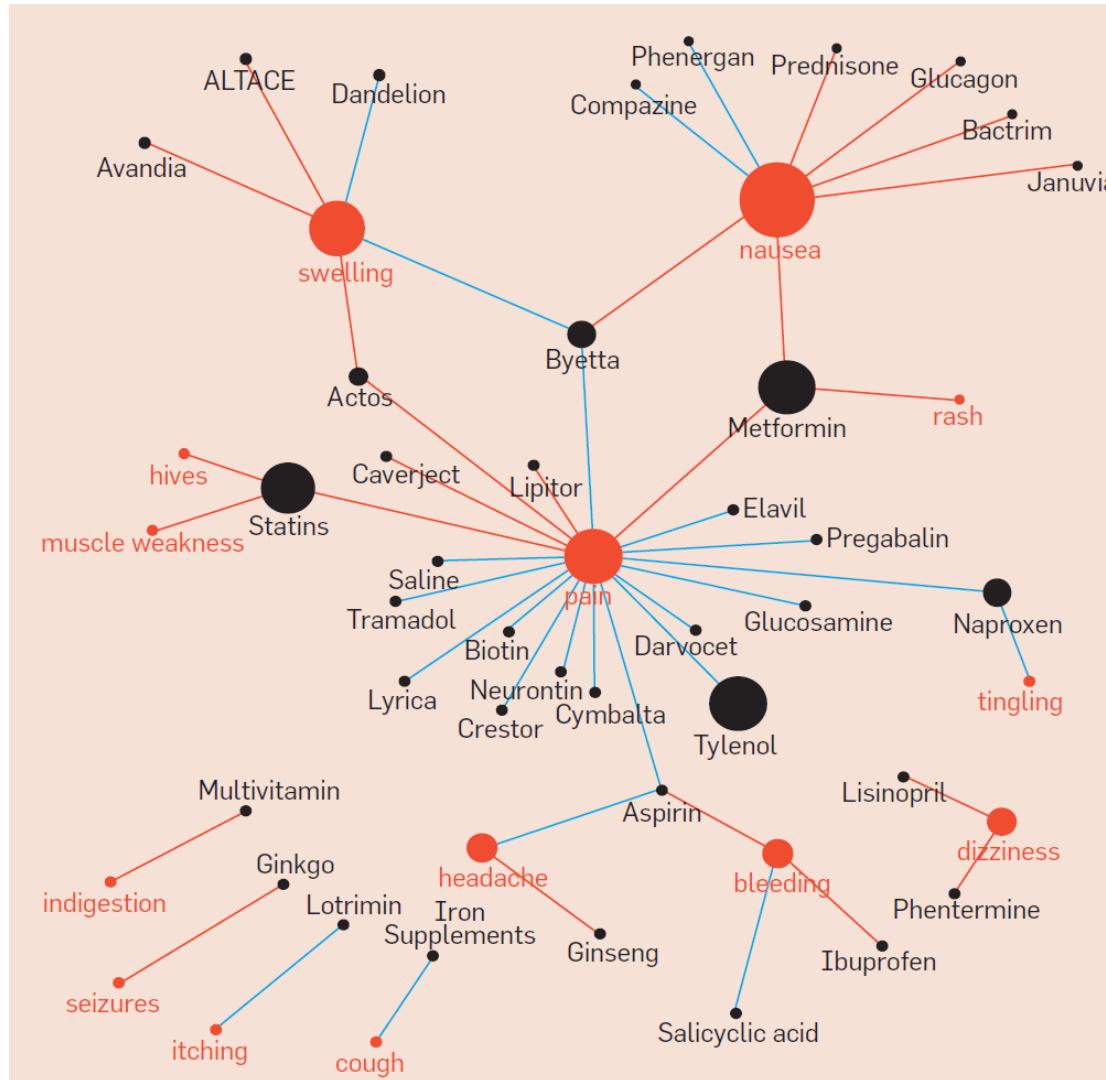
- ✓ Provide general search for opinions

Player	Line	Score	승	패배	피안타	피홈런	볼넷	실점	평균 자책점	이닝당 삼진	이닝당 볼넷	삼진 /볼넷	방어율
웨버	NC웨버는 7이닝 동안 1안타 3볼넷 10탈삼진으로 무실점 호투했다.	0.991	1	0	0	0	1	0	0	1	1	1	0
이재학	이재학 '10승', 3년만에 달라진 위상 증명하다	0.986	1	0	0	1	0	1	0	0	0	1	0
이태양	'이태양 완벽투' NCLG 상대로 창단 첫 스크립트	0.966	1	0	0	0	0	0	0	0	0	1	0
에릭	한편, 이날 7이닝 3실점으로 잘 던지며 7경기 만에 국내 첫 승을 거둔 에릭은 "굉장히 흥분된다."	0.803	1	0	1	0	0	0	0	0	0	0	0
찰리	어이없는 실책 2개가 나오자 찰리는 흔들리기 시작했다.	0.506	0	1	1	1	0	1	0	1	0	1	1
찰리	찰리가 대량 실점을 했지만 그 과정에서 3루수 모창민과 1루수 테임즈의 실책이 동반되면서 자책은 1점 밖에 되지 않았다.	0.506	0	1	1	1	0	1	0	1	0	1	1
원종현	NC 원종현이 패전투수가 됐다.	0.293	0	1	0	0	0	1	1	1	0	1	1
원종현	세 번째 투수로 등판한 원종현 역시 1사후 8번 김성현에게 솔로포를 맞았다.	0.102	0	0	0	1	1	0	1	1	1	0	0
이재학	NC 선발 이재학은 8이닝 8피안타(2홈런) 5탈삼진 3볼넷 2실점을 기록했다.	0.079	0	0	1	1	0	1	1	0	0	0	1
이혜천	이혜천이 올라온 뒤 한꺼번에 5점을 내주면서 맥빠진 경기가 되고 말았다.	0.066	0	0	1	1	0	1	0	0	1	0	0

# Applications

Feldman (2013)

- Relationships between Drugs and Symptoms



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# Problem Definition

Feldman (2013)

## Problem Statement: Abstraction

- Consists of two parts
  - ✓ (1) Opinion definition
    - What is an opinion?
  - ✓ (2) Opinion summarization
    - Opinions are subjective
    - An opinion from a single person (unless a VIP) is often not sufficient for action
    - We need opinions from many people, and thus need to summarize those opinions

# Problem Definition

Feldman (2013)

## Entity and Aspect/Feature

**Id:** Abc123 on 5-1-2008 “I bought an *iPhone* a few days ago. It is such a nice *phone*. The *touch screen* is really cool. The *voice quality* is clear too. It is much better than my old *Blackberry*, which was a terrible *phone* and so *difficult to type* with its *tiny keys*. However, *my mother* was mad with me as I did not tell her before I bought the *phone*. She also thought the *phone* was too *expensive*, ...”

- What do we see?
  - ✓ **Opinion targets:** entities and their features/aspects
  - ✓ **Sentiments:** positive and negative
  - ✓ **Opinion holders:** persons who hold the opinions
  - ✓ **Time:** when opinions are expressed

# Problem Definition

Feldman (2013)

- Two main types of opinions
  - ✓ **Regular opinions:** Sentiment/opinion expressions on some target entities
    - Direct opinions: “The touch screen is really cool.”
    - Indirect opinions: “After taking the drug, my pain has gone.”
  - ✓ **Comparative opinions:** Comparisons of more than one entity
    - “iPhone X is better than Galaxy 9”
  - ✓ Focus more on regular opinions in this lecture

# Problem Definition

Feldman (2013)

- A (Regular) Opinion
  - ✓ An opinion has the following basic components

$$(g_i, so_{ijk}, h_j, t_k)$$

where

- $g_i$  is a target.
- $so_{ijk}$  is the sentiment value (positive, negative, neutral, or a rating score) of the opinion from opinion holder  $h_j$  on target  $g_i$  at time  $t_k$ .
- $h_j$  is an opinion holder.
- $t_k$  is the time when the opinion is expressed.

# Problem Definition

Feldman (2013)

- Opinion Target
  - ✓ In some cases, **opinion target** is a single **entity** or topic.
    - “I love G5” and “I support **tax cut**.”
  - ✓ But in many other cases, it is more complex.
    - “I bought an **iPhone** a few days ago. **It** is such a **nice** phone. **The touch screen** is really **cool**.”
    - Opinion target of the 3<sup>rd</sup> sentence is not just touch screen, but the “touch screen of iPhone”
    - “I support **tax cut** for the middle class, but not for **the rich...**”

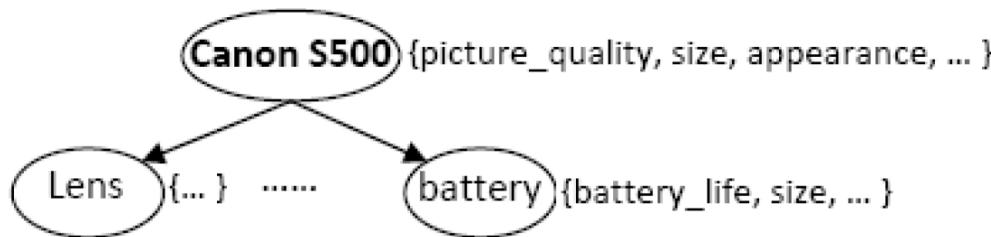
# Problem Definition

Feldman (2013)

- Entity and Aspect

- ✓ Definition of Entity: An **entity e** is a product, person, event, organization, or topic. **e** is represented as

- a hierarchy of **components, sub-components**, and so on.
- Each node represents a component and is associated with a set of **attributes** of the component.



- An opinion can be expressed on any node or attribute of the node.
- For simplicity, we use the term **aspects (features)** to represent both components and attributes.

# Problem Definition

Feldman (2013)

- Definition of an Opinion as a Quintuple

$$(e_i, a_{jl}, so_{ijkl}, h_j, t_k)$$

where

- $e_i$  is a target entity/object
- $a_{jl}$  is an aspect/feature/attribute/facet of the entity  $e_i$
- $so_{ijkl}$  is the sentiment value (positive, negative, neutral, or a rating score) of the opinion from opinion holder (source)  $h_j$  on aspect  $a_{jk}$  of entity  $e_i$  at time  $t_k$
- $h_j$  is an opinion holder
- $t_k$  is the time when the opinion is expressed

# Problem Definition

Feldman (2013)

- Quintuple Opinion Examples

**Id:** Abc123 on 5-1-2008 “I bought an *iPhone* a few days ago. It is such a nice *phone*. The *touch screen* is really cool. The *voice quality* is clear too. It is much better than my old *Blackberry*, which was a terrible *phone* and so *difficult to type* with its *tiny keys*. However, *my mother* was mad with me as I did not tell her before I bought the *phone*. She also thought the *phone* was too *expensive*, ...”

- ✓ (iPhone, General, Positive, Abc123, 5-1-2008)
- ✓ (iPhone, touch\_screen, Positive, Abc123, 5-1-2008)
- ✓ ...

# Problem Definition

Feldman (2013)

## Purpose: Structure the unstructured

- Given an opinionated document,
  - ✓ Discover all quintuples  $(e_i, a_{jl}, so_{ijkl}, h_j, t_k)$
  - ✓ Or, solve some simpler form of the problem
    - E.g. Classify the sentiment of the entire document
  - ✓ With the quintuples, unstructured texts transformed into structured data.

# Rational vs. Emotional Evaluation

Feldman (2013)

- Rational Evaluation
  - ✓ Many evaluation/opinion sentences express no emotion
    - The voice of this phone is clear
- Emotional evaluation
  - I love this phone
- Some emotion sentences express no (positive or negative) opinion/sentiment
  - ✓ I am so surprised to see you

# Abstraction: Opinion Summary

Feldman (2013)

- Feature-based opinion summary

“I bought an *iPhone* a few days ago. It is such a nice *phone*. The *touch screen* is really cool. The *voice quality* is clear too. It is much better than my old *Blackberry*, which was a terrible *phone* and so *difficult to type* with its *tiny keys*. However, *my mother* was mad with me as I did not tell her before I bought the *phone*. She also thought the *phone* was too *expensive*, ...”

1.

....

## Feature Based Summary of iPhone:

### Feature1: Touch screen

Positive: 212

- *The touch screen* was really cool.
- *The touch screen* was so easy to use and can do amazing things.

...

Negative: 6

- The *screen* is easily scratched.
- I have a lot of difficulty in removing finger marks from the *touch screen*.

...

### Feature2: voice quality

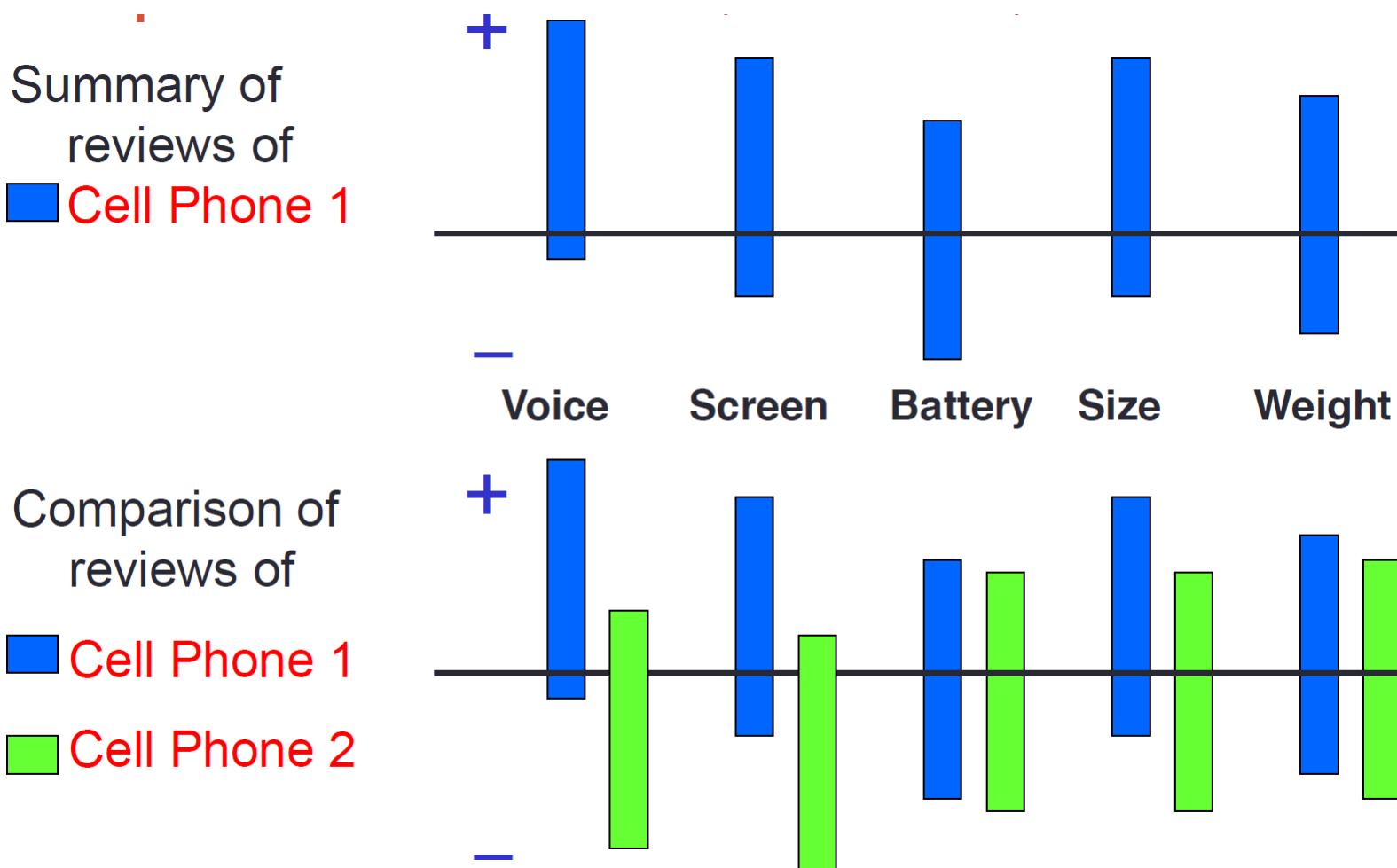
...

*Note: We omit opinion holders*

# Abstraction: Opinion Summary

Feldman (2013)

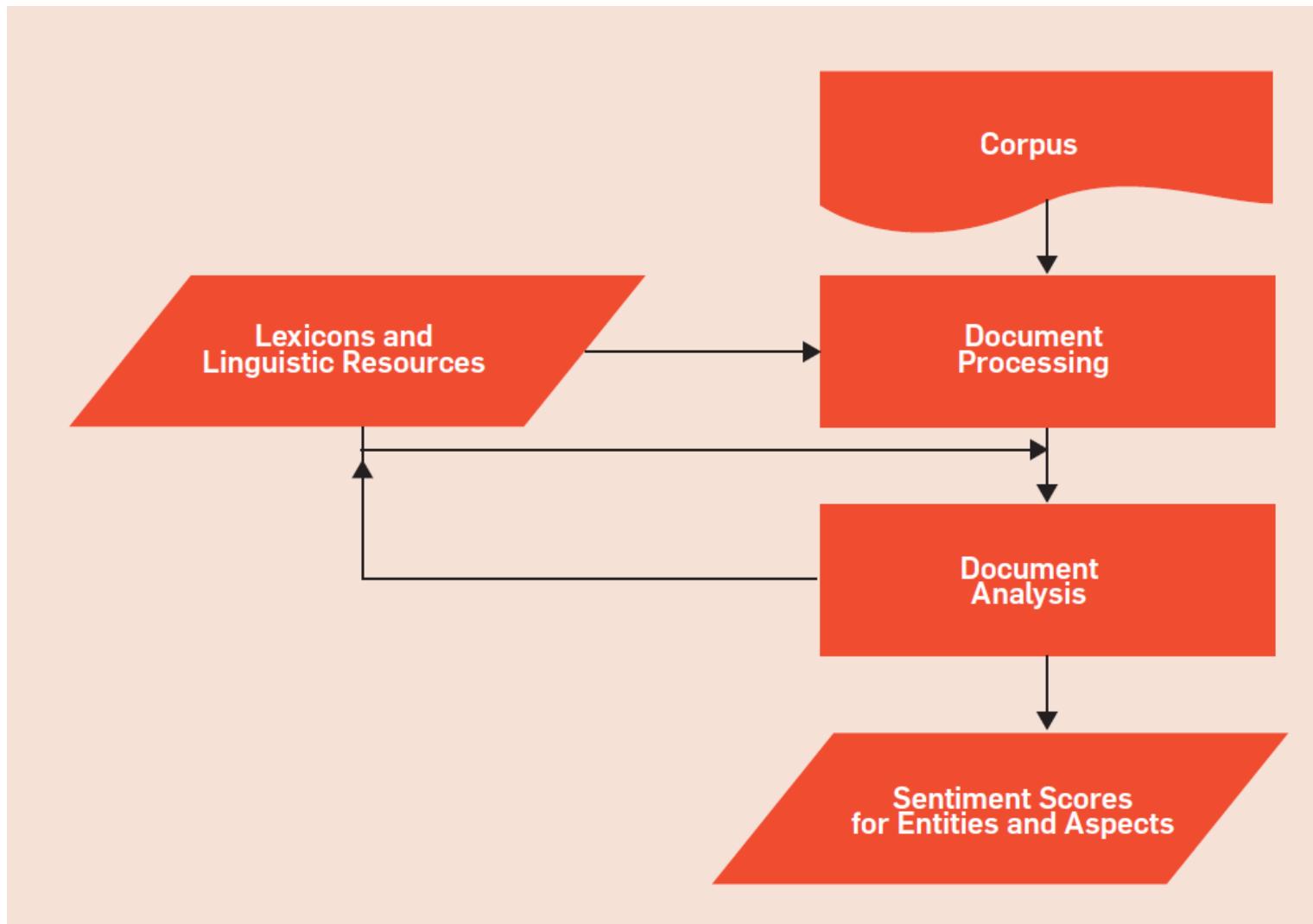
- Opinion Comparison



# Sentiment Analysis Architecture

Feldman (2013)

- Architecture of generic sentiment analysis system



# Document Sentiment Classification

Feldman (2013)

- Document Sentiment Classification

- ✓ Classify a whole opinion document based on the overall sentiment of the opinion holder
  - Classes: **positive**, **negative** (possibly neutral)
  - Neutral or no opinion is hard. Most papers ignore it.
- ✓ It is basically a text classification problem
- ✓ Assumption: a document is written by **a single person** and expresses opinion/sentiment on **a single entity**.
- ✓ Goal: discover **(\_, \_, **so**, \_, \_)** where e, a, h, and t are ignored.
  - Reviews usually satisfy the assumption (4/5 stars → positive, ½ stars → negative)
  - Many forum postings and blogs do not. They can mention and compare multiple entities or they express no sentiments.

# Document Sentiment Classification

Feldman (2013)

- Supervised Learning Formulation
  - ✓ Training and test data: movie reviews with star ratings
    - 4-5 stars as positive and 1-2 stars as negative
    - Neutral is ignored
  - ✓ **Key: feature engineering**
    - Typically unigrams (bag of individual words)
    - Term frequency and different IR weighting schemes
    - Part of speech (POS) tags
    - Opinion words and phrases
    - Negations
    - Syntactic dependency
  - ✓ Too coarse for most applications

# Sentence Sentiment Classification

Feldman (2013)

- Sentence Sentiment Classification
  - ✓ Assumes a single sentiment per sentence
  - ✓ Not always true, so one can classify clauses instead
- Two steps of sentence sentiment classification
  - ✓ Subjectivity classification
    - To identify subjective sentences
  - ✓ Sentence classification of subjective sentences
    - As positive or negative

# Feature/Aspect-based Sentiment Classification

Feldman (2013)

- Document/Sentence level sentiment classification
  - ✓ Useful but do not find **what people liked and disliked**.
  - ✓ They do **not** identify the targets of opinions: entities and their aspects
- Finding entities
  - ✓ Similar to but somewhat different from the traditional named entity recognition (NER)
    - Frequent nouns and noun phrases
    - Rule-based or supervised learning (HMM, CRFs)
    - Double propagation (DP): knowing one helps find the other (an opinion should have a target)
      - Input: a set of seed opinion words
      - The **rooms** are **spacious**
      - The **phone** has **good screen**

# Sentiment Lexicon

- Sentiment Lexicon

✓ Lists of words and expressions used to express people's subjective feelings and sentiment/opinions

- Positive: beautiful, wonderful, good, amazing, ...
- Negative: bad, poor, terrible, ...
- Not just individual words, but also phrases and idioms
- “cost an arm and a leg”

✓ Many of them are context dependent, not just application domain dependent.

- Three main ways to compile such lists

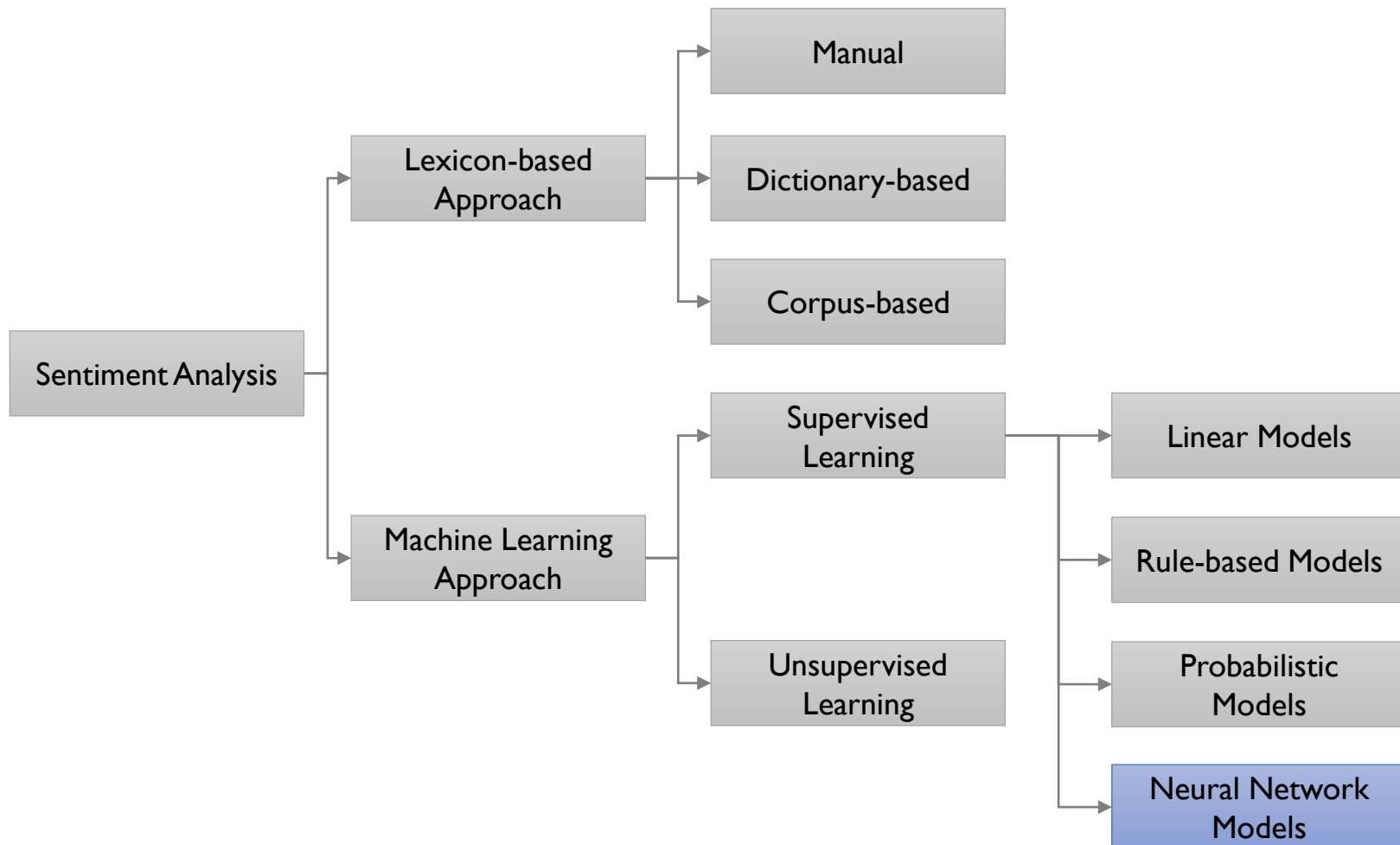
✓ Manual approach: not a bad idea for a one-time effort

✓ Dictionary-based approach

✓ Corpus-based approach

# Sentiment Analysis Approaches

- Sentiment classification techniques



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# Lexicon-based Approach

- 감성 사전 활용

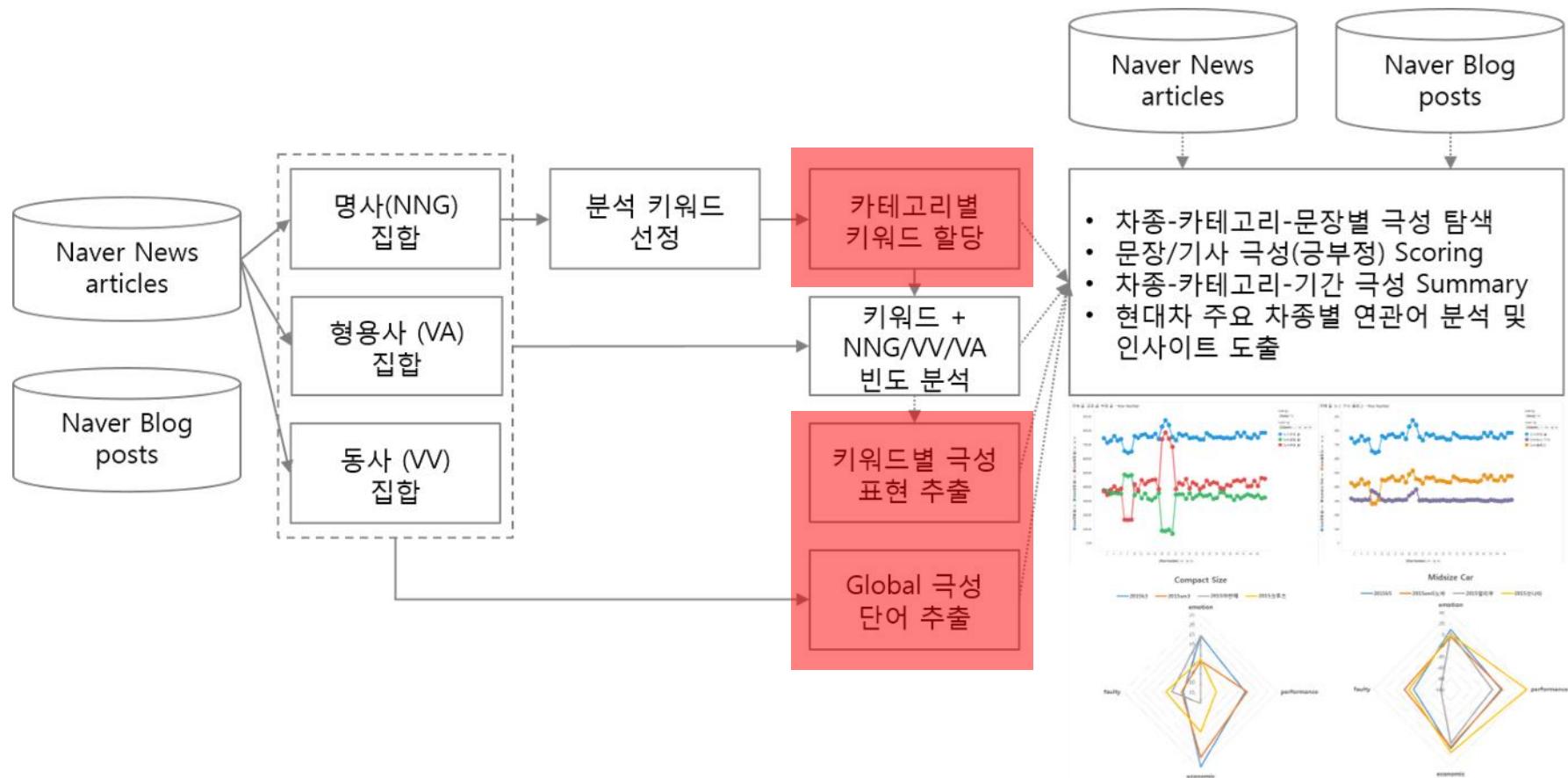
- ✓ 감성 사전은 극성, 주관성 등 감성을 지닌 감성 어휘들의 모음
- ✓ 대부분 영어에 대한 감성 사전이 구축 (ex. SentiWordNet)
- ✓ 한국어의 경우 준지도학습을 통해 감성 사전을 구축하려는 시도가 있었음 (서덕성 외, 2017)
- ✓ 문서 또는 문장을 구성하는 단어의 감성 점수를 사용하여 비지도학습 기반 감성 분석을 진행할 수 있음

긍정		부정	
단어	감성 점수	단어	감성 점수
슬펐	1	별루였어	-0.5458
괜찮	0.5956	드럽	-0.4140
신나요	0.4357	부족	-0.3713
눈시울	0.4089	심해	-0.3449
짱	0.4002	어설퍼	-0.3123
존잘	0.3851	빈약	-0.2531

감성사전 예시 (출처: 서덕성 외, 2017)

# Manual Approach

- Sentiment Analysis for Car Models



# Manual Approach

## • Data Collection

✓ News articles and blog posts from NAVER (2010.01.01 ~ 2015.07.31)

원본 기사/블로그 게시글 검색

웹 크롤러를 이용한 게시글 수집

article_date	title	sentence_id	sentence
2010-01-04	2009 '베스트셀링카'는 쏘나타	2	(서울=연합뉴스) 권혁창 기자 = 지난해 국내에서 가장 많이 팔린 베스트셀링카는 현대차의 쏘나타로 나타났다
2010-01-04	34일 관련업계에 따르면 현대차 쏘나타는 지난 한해 구형 NF 8만4천981대, 신형 YF 6만1천345대 등 총 14만6천326대가 팔려 준중형 아반떼(11만5천378대)를 누르고 내수 판매 1위를 차지했다.	3	4일 관련업계에 따르면 현대차 쏘나타는 지난해 9월 출시된 이후 매달 판매 1위를 차지하고 있다. 특히 신형 쏘나타는 지난해 9월 출시된 이후 매달 판매 1위를 차지하고 있다.
2010-01-04	4동력 신형 쏘나타는 지난해 9월 출시된 이후 매달 판매 1위를 차지하고 있다.	4	9일 아울렛 차량 판매량은 40만2천592대로 3년 연속 올랐으며, 현대차의 아울렛 차량 판매는 7만8천946대로 4년 연속 올랐다.
2010-01-04	6이어 현대차 그랜저(7만5천944대), 산타페(5만8천324대), 르노삼성 SM5(4만5천906대)가 5~7위를 차지했다.	5	6이어 현대차 그랜저(7만5천944대), 산타페(5만8천324대), 르노삼성 SM5(4만5천906대)가 5~7위를 차지했다.
2010-01-04	7기아 포르테(5만1천374대), 로체(4만9천374대), 르노삼성 SM4(4만5천906대), GM대우 라세티 프리미어(4만4천464대)가 그 뒤를 이었다.	6	7기아 포르테(5만1천374대), 로체(4만9천374대), 르노삼성 SM4(4만5천906대), GM대우 라세티 프리미어(4만4천464대)가 그 뒤를 이었다.
2010-01-04	8faith@yna.co.kr	7	8faith@yna.co.kr
2010-01-04	9[관련기사]	8	[관련기사]
2010-01-04	10<저작권자(C)연합뉴스	9	<저작권자(C)연합뉴스
2010-01-04	11무단전재·재배포금지,>	10	무단전재·재배포금지,>

데이터베이스에 Raw Data를 저장

34/90

# Manual Approach

- Data Collection: 520,000 news articles & 2,360,000 blog posts
  - ✓ At least 10,000 and at most 38,000 news articles are collected for each model
  - ✓ At least 89,000 and at most 248,000 blog posts are collected for each model

원본 문장	형태소 분석 결과
지난해 국내에서 가장 많이 팔린 베스트셀링카는 현대차의 쏘나타로 나타났다.	지난해(NNG) 국내(NNG) 팔리(VV) 베스트(NNG) 셀링카(NNG) 현대(NNG) 차(NNG) 쏘나타(NNG) 나타나(VV)
4일 관련업계에 따르면 현대차 쏘나타는 지난 한해 구형 NF 8만4천981대, 신형 YF 6만1천345대 등 총 14만6천326대가 팔려 준중형 아반떼(11만5천378대)를 누르고 내수 판매 1위를 차지했다.	관련(NNG) 업계(NNG) 따르(VV) 현대(NNG) 차(NNG) 쏘나타(NNG) 지나(VV) 한해(NNG) 구형(NNG) 신형(NNG) 팔리(VV) 중형(NNG) 아반떼(NNG) 누르(VV) 내수(NNG) 판매(NNG) 차지(NNG)
특히 신형 쏘나타는 지난해 9월 출시된 이후 매달 1만5천대 이상 팔려나가며 현대차의 내수판매 증대를 이끌었다.	신(NNG) 형(NNG) 쏘나타(NNG) 지난해(NNG) 출시(NNG) 이후(NNG) 매달(NNG) 이상(NNG) 팔(VV) 나가(VV) 현대(NNG) 차(NNG) 내수(NNG) 판매(NNG) 증대(NNG) 이끌(VV)
기아차의 경차 모닝은 10만2천82대로 3위에 올랐으며, 현대차의 소형 트럭 포터가 7만8천846대로 4위에 랭크됐다.	기아(NNG) 차(NNG) 경차(NNG) 모닝(NNG) 오르(VV) 현대(NNG) 차(NNG) 소형(NNG) 트럭(NNG) 포터(NNG) 랭크(NNG)
이어 현대차 그랜저(7만5천844대), 싼타페(5만8천324대), 르노삼성 SM5(6만1천10대)가 5~7위를 차지했다.	잇(VV) 현대(NNG) 차(NNG) 그랜저(NNG) 싼타페(VA) 타(NNG) 르노(NNG) 삼성(NNG) SM5(NNG) 가(VV) 차지(NNG)
기아차 포르테(5만1천374대), 로체(4만9천54대), 르노삼성 SM3(4만5천906대), GM대우 라세티 프리미어(4만4천464대)가 그 뒤를 이었다.	기아(NNG) 차(NNG) 포르테(NNG) 로체(NNG) 르노(NNG) 삼성(NNG) SM3(NNG) 대우(NNG) 라세티(NNG) 프리미어(NNG) 가(VV) 뒤(NNG) 잇(VV)

# Manual Approach

- Keyword selection and sentiment dictionary construction

✓ Purely done by X people within 7 days

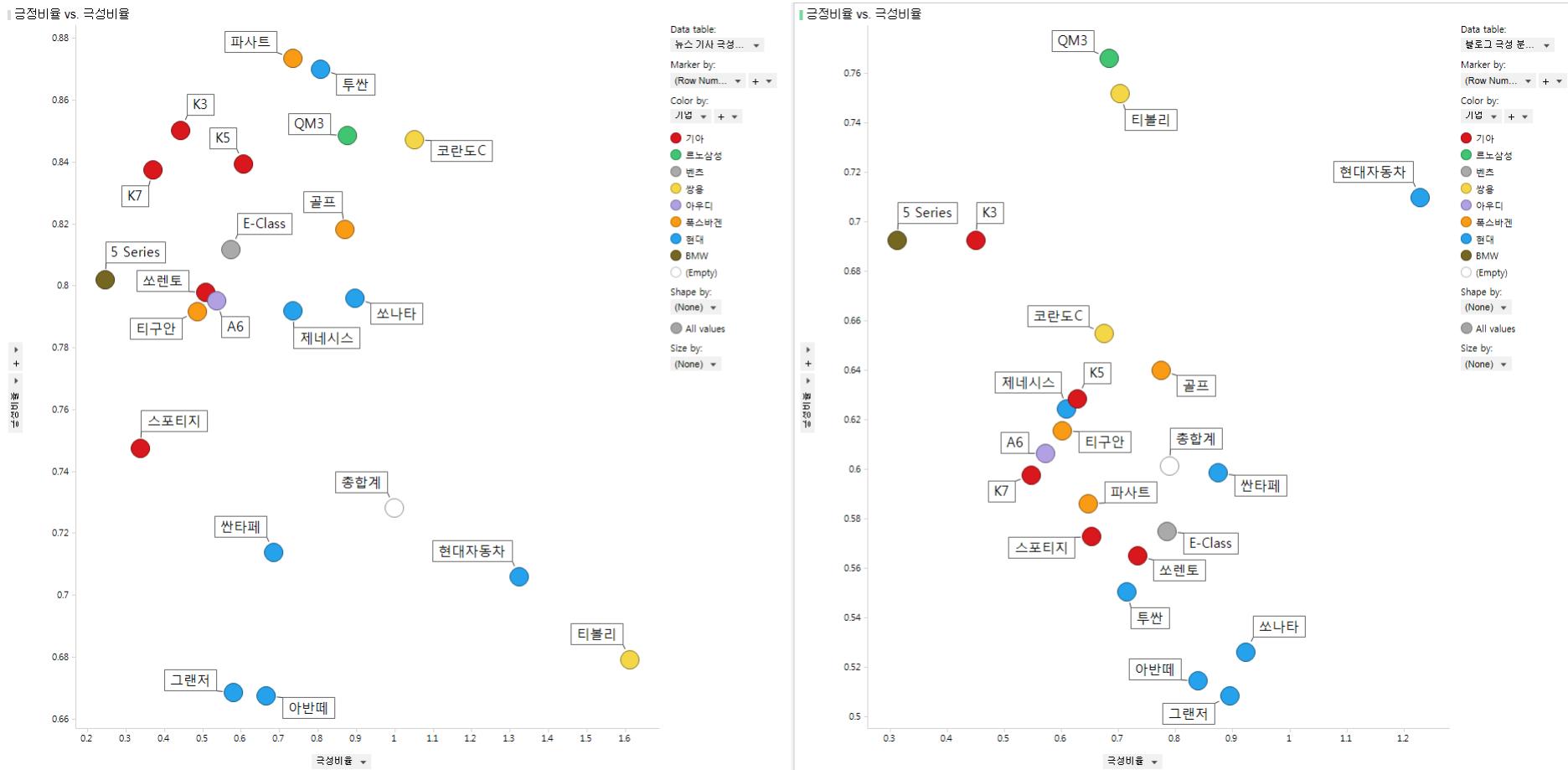
카테고리	키워드	키워드+표현	극성
Performance	기술	기술 갖(VV)	Positive
Economic	시장	시장 티볼리(NNG)	Negative
Reputation	노사	노사 연속 파업(NNG)	Negative
Performance	엔진	엔진 선택 있(VV)	Positive
Economic	매출	매출 하락(NNG)	Negative
Reputation	직원	직원 노동 조합(NNG)	Negative
Performance	하이브리드	하이브리드 고객(NNG)	Positive
Faulty	경보	경보 장치 급제동(NNG)	Positive
Performance	마력	마력 엔진 장착(NNG)	Positive
Economic	경영	경영 환경 악화(NNG)	Negative
Emotional	프리미엄	프리미엄 이미지(NNG)	Positive
Emotional	사양	사양 정숙(NNG)	Positive
Economic	시장	시장 다변화(NNG)	Positive
Emotional	출시	출시 스포츠(NNG)	Positive
Economic	시장	시장 판매 증가율(NNG)	Positive
Economic	환경	환경 차량 선보이(VV)	Positive
Emotional	콘셉트	콘셉트 세계 최초(NNG)	Positive
Reputation	노동자	노동자 정규직 전환 촉구(NNG)	Negative
...	...	...	...



"문제는 한국 사회에서 시스템이 필요하다고 지시를 내릴 사람은 많은데 전통적으로 “노가다”를 뛸 사람은 없다는 겁니다. 이런 일은 남이 해야 하는 거라 생각하죠. 아니면 남이 했다가 자기한테 해가 되면 안 되니까 오만 가지 이유를 대서 이런 일은 하면 안 된다고 하고, 이런 일이 의료계에서만 있는 줄 알았어요. 사회 전반이 바뀌지 않으면 이 문제는 나아지지 않아요"라고 했다.

# Manual Approach

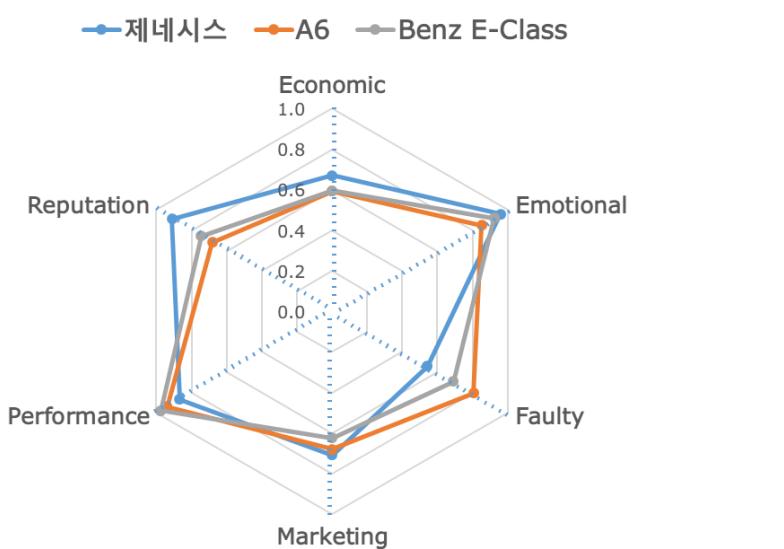
- Sentiment Analysis Results



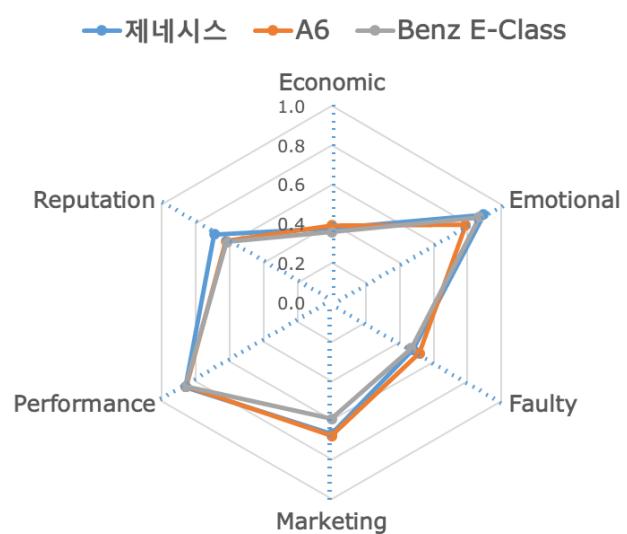
# Manual Approach

- Sentiment Analysis Results

뉴스

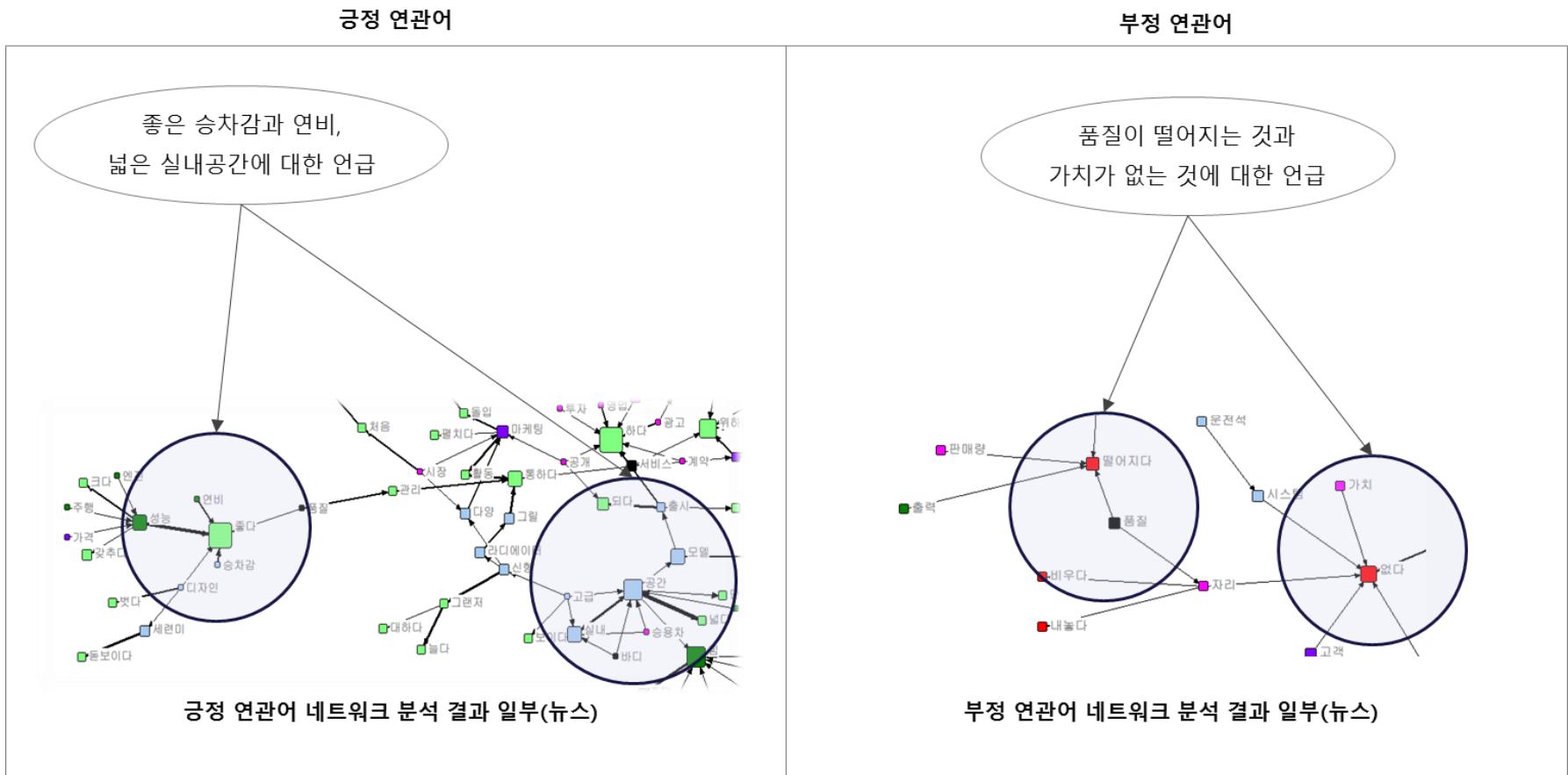


블로그



# Manual Approach

- Sentiment Analysis Results



# Dictionary- vs Corpus-based Approaches

Feldman (2013)

- Dictionary-based approaches
  - ✓ Typically use WordNet's synsets and hierarchies to acquire opinion words
    - Start with a small seed set of opinion words
  - ✓ Usually do not give domain or context dependent meanings
- Corpus-based approaches
  - ✓ Often use a double propagation between opinion words and the items they modify
    - Knowing an aspect can find the opinion word that modifies it
      - The rooms are *spacious*
    - Knowing some opinion words can find more opinion words
      - The rooms are *spacious* and *beautiful*
  - ✓ Can find domain dependent orientations
  - ✓ Require a large corpus to get good coverage

# Dictionary-based Approaches

- Popular Sentiment Lexicon Database for English

**M** Multi-Perspective Question Answering  
**P** Subj. Perspective  
**A** Question Answering

**Main** MPQA Home    **Corpora** News, debates, etc.    **Lexicons** Subj. clues, etc.    **Annotation** GATE, MPQA, gfof    **OpinionFinder** Subjectivity detector

**MPQA Opinion Corpus**  
**Subjectivity Lexicon**  
**Subj. Sense Annotations**  
**Arguing Lexicon**  
**+/-Effect Lexicon**  
**Product Debate Data**  
**Political Debate Data**  
**goodFor/badFor Data**  
**OpinionFinder System**

PLEASE NOTE: our URL has recently changed from [www.cs.pitt.edu/mpqa/](http://www.cs.pitt.edu/mpqa/) to [mpqa.cs.pitt.edu](http://mpqa.cs.pitt.edu). Please update your bookmarks accordingly.

- MPQA Opinion Corpus
  - [MPQA Opinion Corpus](#)
  - The MPQA Opinion Corpus contains news articles from a wide variety of news sources manually annotated for opinions and other private states (i.e., beliefs, emotions, sentiments, speculations, etc.). To download the MPQA Opinion Corpus click [here](#).
  - For sample documents and instructions for MPQA annotation in GATE, click [here](#). Updated July 2011.
  - To learn more about the subjectivity and sentiment research that produced MPQA, please refer to the following publications:
    - Janyce Wiebe, Theresa Wilson , and Claire Cardie (2005). [Annotating expressions of opinions and emotions in language](#). *Language Resources and Evaluation*. volume 39, issue 2-3, pp. 165-210.
    - Theresa Wilson (2008). [Fine-Grained Subjectivity Analysis](#). PhD Dissertation. Intelligent Systems Program, University of Pittsburgh.
    - Lingjia Deng and Janyce Wiebe (2015). [MPQA 3.0: An Entity/Event-Level Sentiment Corpus](#). NAACL-HLT, 2015.
- Subjectivity Lexicon
  - Made available under the terms of [GNU General Public License](#). They are distributed without any warranty.
  - The Subjectivity Lexicon (list of subjectivity clues) that is part of OpinionFinder is also available for separate [download](#). These clues were compiled from several sources (see the enclosed README). This is the version of the lexicon used in:
    - Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). [Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis](#). Proc. of HLT-EMNLP-2005.

<http://mpqa.cs.pitt.edu/>



SentiWordNet is a lexical resource for opinion mining. SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity, objectivity. SentiWordNet is described in details in the papers:

[SentiWordNet: A Publicly Available Lexical Resource for Opinion Mining](#)  
[SentiWordNet 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining](#)

## How to obtain SentiWordNet

The current "official" version of SentiWordNet is 3.0, which is based on [WordNet 3.0](#).

SentiWordNet is distributed under the [Attribution-ShareAlike 3.0 Unported \(CC BY-SA 3.0\) license](#). Among the other possibilities, this license allows the use of SentiWordNet in commercial applications, provided that the application mentions the use of SentiWordNet and SentiWordNet is attributed to its authors.

[Click here to download SentiWordnet 3.0](#)

## micro-WordNet-Opinion 3.0

[micro-WordNet-Opinion 3.0](#) is the automatic mapping of the [micro-WordNet-Opinion corpus](#) to WordNet 3.0.

## SentiWordNet has been used in...

Check [Google](#) for a list of the papers that use SentiWordNet 3.0

Check [Google](#) for a list of the papers that use SentiWordNet 1.0

<http://sentiwordnet.isti.cnr.it/>

# Dictionary-based Approaches

- Popular Sentiment Lexicon Database for English

## Opinion Lexicon (or Sentiment Lexicon)

- Opinion Lexicon:** A list of English positive and negative opinion words or sentiment words (around 6800 words). This list was compiled over many years starting from our first paper (Hu and Liu, KDD-2004).
- Comparative words:** A list of non-standard English comparative words and phrases for sentiment analysis. This list was compiled over many years starting from our first paper (Jindal and Liu, SIGIR-2006)
- Although necessary, having an opinion lexicon is far from sufficient for accurate sentiment analysis. See this paper: [Sentiment Analysis and Subjectivity](#) or the [Sentiment Analysis](#) book.
- Try [Search for the Best Restaurant](#) based on specific aspects, e.g., "best burger," "friendliest service." The system is a demo, which uses the lexicon (also phrases) and grammatical analysis for opinion mining.

## Data Sets

- Annotated:** [Customer Review Datasets \(5 products\)](#) associated with the paper (Hu and Liu, KDD-2004).
- Annotated:** [Additional Customer Review Datasets \(9 products\)](#) some used in (Ding, Liu and Yu, WSDM-2008), which improves the lexicon-based method proposed in (Hu and Liu, KDD-2004)
- Annotated:** [More Customer Review Datasets \(3 products\)](#) used in (Liu et al., IJCAI-2015)
- Amazon Product Review Data (more than 5.8 million reviews)** used in (Jindal and Liu, WWW-2007; WSDM-2008; Lim et al., CIKM-2010; Jindal, Liu and Lim, CIKM-2010; Mukherjee et al. WWW-2011; Mukherjee, Liu and Glance, WWW-2012) for opinion spam (fake review) detection. You can also use it for sentiment analysis. It has information about reviewers, review texts, ratings, product info, etc. Due to the large file size, you may need to use [Download Accelerator Plus \(DAP\)](#) to download. If you use this data, please cite ([Jindal and Liu, WSDM-2008](#)).
- Pros and cons dataset** used in (Ganapathibhotla and Liu, Coling-2008) for determining context (aspect) dependent sentiment words, which are then applied to sentiment analysis of comparative sentences ([comparative sentence dataset](#)). The same form of Pros and Cons data was also used in (Liu, Hu and Cheng, WWW-2005).
- Comparative sentence dataset** used in (Jindal and Liu, SIGIR-06) and (Jindal and Liu, AAAI-2006). [Comparative sentence dataset](#) used in (Ganapathibhotla and Liu, Coling-2008).
- Blog author gender classification data set** associated with the paper (Mukherjee and Liu, EMNLP-2010)
- Debate data set** used in (Mukherjee and Liu, ACL-2013; Mukherjee et al. ACL-2013 ).
- Yelp Filtered Reviews** for Opinion spam or fake detection associated with the paper (Mukherjee et al. ICWSM-2013).

[https://www.cs.uic.edu/~liub/FBS/  
sentiment-analysis.html#lexicon](https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon)

## SenticNet

Helping machines to  
learn, leverage, love.

about  
downloads

sentic computing  
publications

demo  
projects

sentic api  
team

Talking about SenticNet is talking about concept-level sentiment analysis, that is, performing tasks such as polarity detection and emotion recognition by leveraging on semantics and linguistics instead of solely relying on word co-occurrence frequencies.

In this context, SenticNet can be one of the following things:

- 1) a concept-level knowledge base;
- 2) a multi-disciplinary framework;
- 3) a private company.



As a **knowledge base**, SenticNet provides a set of semantics, sentics, and polarity associated with 50,000 natural language concepts. In particular, semantics are concepts that are most semantically-related to the input concept (i.e., the five concepts that share more semantic features with the input concept), sentics are emotion categorization values expressed in terms of four affective dimensions (Pleasantness, Attention, Sensitivity, and Aptitude) and polarity is floating number between -1 and +1 (where -1 is extreme negativity and +1 is extreme positivity). The knowledge base is downloadable for free as a standalone XML file and its latest version (released every two years) is also accessible as an API.

As a **framework**, SenticNet consists of a set of tools and techniques for sentiment analysis combining commonsense reasoning, psychology, linguistics, and machine learning. In this context, SenticNet is more commonly referred to as **sentic computing**, a multi-disciplinary paradigm that goes beyond mere statistical approaches to sentiment analysis by focusing on a semantic-preserving representation of natural language concepts and on sentence structure.

As a **company**, finally, SenticNet puts together the latest findings in concept-level sentiment analysis to offer easy-to-use state-of-the-art tools for big social data analysis that enable the automation of tasks such as brand positioning, trend discovery, and social media marketing in different modalities.

<http://sentic.net/>

# Dictionary-based Approaches

- SocialSent (Hamilton et al., 2016)

## SocialSent: Domain-Specific Sentiment Lexicons for Computational Social Science

William L. Hamilton, Kevin Clark, Jure Leskovec, Dan Jurafsky

### Introduction

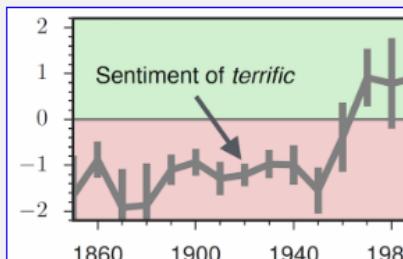
The word *soft* may evoke positive connotations of warmth and cuddliness in many contexts, but calling a hockey player *soft* would be an insult. If you were to say something was *terrific* in the 1800s, this would probably imply that it was terrifying and awe-inspiring; today, *terrific* basically just implies that something is (pretty) good.

A word's sentiment or connotation depends on the domain or context in which it is used. However, previous computational work in natural language processing largely ignores this issue, and focuses on building and deploying generic domain-general sentiment lexicons.

SocialSent is a collection of code and datasets for performing *domain-specific* sentiment analysis. The SocialSent code package contains the SentProp algorithm for inducing domain-specific sentiment lexicons from unlabeled text, as well as a number of baseline algorithms.

We have also released domain-specific historical sentiment lexicons for 150 years of English and community-specific sentiment lexicons for 250 " subreddit" communities from reddit.com. The historical lexicons reveal that more than 5% of sentiment-bearing words switched their polarity from 1850 to 2000, and the community-specific lexicons highlight how sentiment varies drastically between online communities.

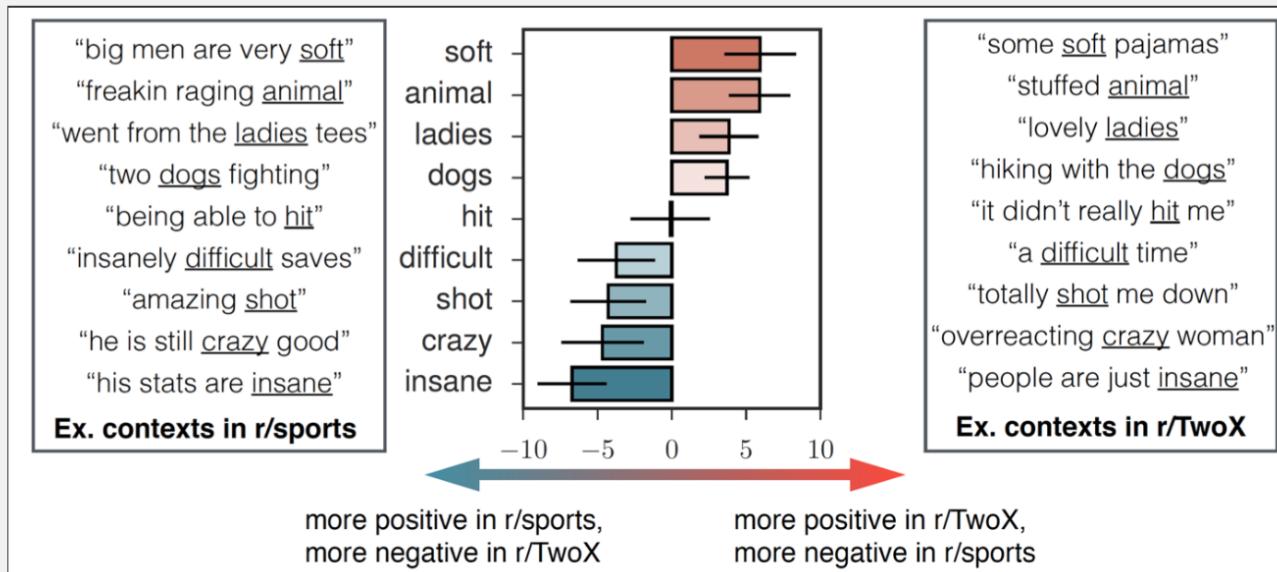
The paper [Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora](#) details the SentProp algorithm and describes the lexicons we induced.



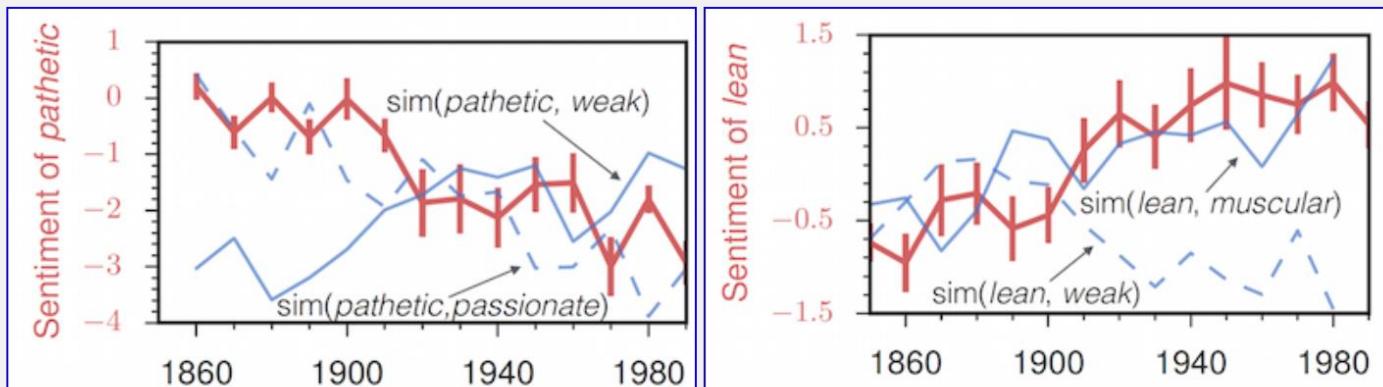
# Dictionary-based Approaches

- SocialSent Highlights

1. Word sentiment varies drastically between online communities



2. Word sentiment varies dramatically over historical time-periods



# Dictionary-based Approaches

- Kaggle??

The screenshot shows a Kaggle dataset page for "Sentiment Lexicons for 81 Languages". The page has a dark background with a blurred image of people in the background. At the top left is a "Dataset" icon. In the top right corner, there is a button with a downward arrow and the number "61". Below the title, it says "Sentiment Polarity Lexicons (Positive vs. Negative)". A profile picture of Rachael Tatman is shown, with the text "Rachael Tatman • updated 2 years ago (Version 1)". Below the author information are tabs for "Data" (which is underlined), "Kernels (1)", "Discussion (3)", "Activity", and "Metadata". To the right of these tabs are "Download (785 KB)" and a "New Kernel" button. There is also a three-dot menu icon. Below the tabs, there are two categories: "Other (specified in description)" and "linguistics, languages". A "Description" section follows, containing a "Context:" heading and a detailed paragraph about sentiment analysis. A "Content:" heading is present, followed by a detailed paragraph about the dataset's generation via graph propagation. At the bottom, there is a "Data (785 KB)" section with a table showing "Data Sources" (including "correctedMetadata.csv" and "sentiment-lexicons.zip"), "About this file" (describing the languages included), and "Columns" (listing "#", "Wikipedia.Language.Code", "Language.name..English.", "Language.name..native.", and "Last.Updated").

Sentiment Lexicons for 81 Languages

Sentiment Polarity Lexicons (Positive vs. Negative)

Rachael Tatman • updated 2 years ago (Version 1)

Data Kernels (1) Discussion (3) Activity Metadata Download (785 KB) New Kernel :

Other (specified in description) linguistics, languages

Description

**Context:**

Sentiment analysis, the task of automatically detecting whether a piece of text is positive or negative, generally relies on a hand-curated list of words with positive sentiment (good, great, awesome) and negative sentiment (bad, gross, awful). This dataset contains both positive and negative sentiment lexicons for 81 languages.

**Content:**

The sentiment lexicons in this dataset were generated via graph propagation based on a knowledge graph—a graphical representation of real-world entities and the links between them. The general intuition is that words which are closely linked on a knowledge graph

▼

Data (785 KB)

Data Sources	About this file	Columns
correctedMetadata.csv 81 x 5 sentiment-lexicons.zip	Information about the languages included in this dataset.	# Wikipedia.Language.Code Language.name..English. Language.name..native. Last.Updated

# Dictionary-based Approaches

- Sentiment Lexicons by Kaggle

✓ 883 positive lexicons, 1,235 negative lexicons for Korean

Positive lexicon examples

같은	정치	상	원하는	위로
더	자기	혁명	적절한	진정한
큰	고려	미	주요한	시인
주	쉽게	충분히	풍부한	일찍이
같이	최고의	아름다운	우수한	신성
매우	강력한	구조	전형적인	작업
잘	뛰어난	오른쪽	자유롭게	후한
볼	사람	상당한	특징	성공한
다양한	유명하다	지원	이해	고급
중요한	아주	단순한	장관	사람
금	대	역사적	충분한	성공적으로
프로	개인	새롭게	참여	좋다
관련	자유	보호	비밀	유지
좋은	상당히	슈퍼	단일	수정
하다	초	지도	오른	보물
금	빠른	지속적으로	훌륭한	개혁
곧	기술	미리	종류	평화
시의	젊은	완전한	계약	힘든
유명한	right	정확히	막대한	변호사
비슷한	넓은	즉시	완전	사전
보다	인물	밝은	좋아하는	뜨거운
전체	특별한	전용	활발한	순수한
최고	德	크다	통일	굉장히
네	거대한	기능	꽤	지배
현대	정확한	방법	별의	강화
단	깊은	빨리	연	명예
사용할	양	진행	분명히	가능
강한	점	강하게	특유의	챔피언
선	원	간단한	승리	자차
작품	수상	해방	쉬운	성과

Negative lexicon examples

의	섬의	소수	지정	수상한
한	갑자기	시험	떨어지는	제외
다른	사망	어두운	문제의	힘
토론	독특한	전자	엄격한	포
특히	죽었다	결정	부족	지는
뒤	공격	죽을	분리	항구
없는	잘못된	비판	끊임없이	개인적으로
해	정의	상대	주장	폐지
없다	전쟁의	잃은	발견	테러
성	복잡한	무거운	분석	수사
크게	피해	향	타격	실패한
주의	부인	부족한	죽음	항의
만든	대상	나쁜	금지	고정
기타	적	길	암살	치열한
지방	잘못	기	김	분할
쓴	붙어	가난한	평범한	충돌
차단	아래의	화가	위험한	계승
긴	상태	색	줄거리	심하게
전혀	열	보지	소리	고문
삭제	강제	친일파	불법	위반
죽은	대신에	가을	분쟁	반란
문제	좁은	가상	연기	바이러스
사용하여	적의	노예	부하	정지
소설	뒤로	어렵다	붕괴	가사
신	발생	다리를	뚜렷한	가짜
본래	거친	경쟁	불가능한	부상
제작	약한	걸려	격렬한	살인
만화	칼	연결	범죄	망명
어려운	발표	회의	말기	짐
반대	지나치게	제한	잃었다	읽을

# Dictionary-based Approaches

Feldman (2013)

- Dictionary-based Approach: Example

✓ <http://ws4jdemos.appspot.com/>

## WS4J Demo

WS4J (WordNet Similarity for Java) measures semantic similarity/relatedness between words.

Type in texts below, or use: [example words](#) [example sentences](#)

1.	Input mode	<input checked="" type="radio"/> Word <input type="radio"/> Sentence
2.	Word 1	love
3.	Word 2	like#
4.	Submit	<input type="button" value="Calculate Semantic Similarity"/>

## Summary

wup( love#v#2 , like#v#2 ) = 0.8000

jcn( love#v#2 , like#v#2 ) = 0.7566

lch( love#v#2 , like#v#2 ) = 2.6391

lin( love#v#2 , like#v#2 ) = 0.9086

res( love#v#2 , like#v#2 ) = 6.5662

path( love#v#2 , like#v#2 ) = 0.5000

lesk( love#v#2 , like#v#2 ) = 28

hso( love#v#2 , like#v#2 ) = 4

Each score above is the highest from 10 x 11 pairs of synsets.

## WS4J Demo

WS4J (WordNet Similarity for Java) measures semantic similarity/relatedness between words.

Type in texts below, or use: [example words](#) [example sentences](#)

1.	Input mode	<input checked="" type="radio"/> Word <input type="radio"/> Sentence
2.	Word 1	fantastic
3.	Word 2	terrible
4.	Submit	<input type="button" value="Calculate Semantic Similarity"/>

## Summary

wup( fantastic , terrible ) = -1 [Unsupported POS Pairs]

jcn( fantastic , terrible ) = -1 [Unsupported POS Pairs]

lch( fantastic , terrible ) = -1 [Unsupported POS Pairs]

lin( fantastic , terrible ) = -1 [Unsupported POS Pairs]

res( fantastic , terrible ) = -1 [Unsupported POS Pairs]

path( fantastic , terrible ) = -1 [Unsupported POS Pairs]

lesk( fantastic#a#2 , terrible#a#4 ) = 153

hso( fantastic#a#2 , terrible#a#4 ) = 6

Each score above is the highest from 5 x 4 pairs of synsets.

# Corpus-based Approaches

Hur et al. (2016)

- Building Up a Sentiment Dictionary based on Movie Review Data

관람 후(678)		관람 전(33)		전체보기 ↗
★★★★★ 9	내게 처음인 무성영화였다. 이렇게 5감을 쓸어가면서 집중하여 본건 처음인 것 같다	widekk3	2012.03.19	신고
★★★★★ 7	한편의 좋은 옛날 영화를 보는 느낌!이지만 개인적으로 이런 영화는 좋아하지 않아서	bbollock	2012.03.19	신고
★★★★★ 9	단순한 스토리지만 탄탄하게 잘 만든 듯. 다만 약간 길었다는 느낌..	un5166	2012.03.18	신고
★★★★★ 9	고전적이고 뻔한 이야기? 이 시대에 무성 영화란 기획 자체가 뛰어난 발상이다.	im_loen	2012.03.18	신고
★★★★★ 9	초심으로 돌아간 영화가 선사하는 마법	brego1114	2012.03.17	신고
★★★★★ 8	시나리오나연출은매우단순해도...극장에서흑백영화,무성영화를본 자체가좋은경험이었음	irlagywlsi	2012.03.17	신고
★★★★★ 10	영화도예술이군요^^	cysuk2	2012.03.17	신고
★★★★★ 8	틀리지 않아도 느낄 수 있다	blesspooh	2012.03.17	신고
★★★★★ 8	3D시대에 무성 흑백 4:3화면의 도전만하는 감독이 신선하다	haurifufang	2012.03.17	신고
★★★★★ 10	영화의 역사를 관통하는 영리한 연출과 무성영화의 미덕을 새삼 느끼게 해준다	luki48	2012.03.17	신고

# Corpus-based Approaches

Hur et al. (2016)

- Building Up a Sentiment Dictionary based on Movie Review Data
  - ✓ T-test for testing the difference of review ratings with and without a word

$$R(r_{i,j}, w_q) = \begin{cases} 0 & \text{if } w_q \notin r_{i,j} \\ r(r_{i,j}) & \text{if } w_q \in r_{i,j} \end{cases}$$

$$Score(w_q) = E(w_q) = \frac{1}{n(w_q)} \sum_{i=1}^m \left( \sum_{j=1}^{n_i} R(r_{i,j}, w_q) \right)$$

$$Var(w_q) = \frac{1}{n(w_q) - 1} \sum_{i=1}^m \left( \sum_{j=1}^{n_i} (R(r_{i,j}, w_q) - Score(w_q))^2 \right)$$

# Corpus-based Approaches

Hur et al. (2016)

- Building Up a Sentiment Dictionary based on Movie Review Data
  - ✓ T-test for testing the difference of review ratings with and without a word

$$\text{Testing : } T_w = \frac{E(W) - E(w)}{\sqrt{\frac{s_W^2}{n(W)} + \frac{s_w^2}{n(w)}}} \quad \begin{cases} \text{Positive if} & T_w > t_{(\alpha;v)} \\ \text{Negative if} & T_w < -t_{(\alpha;v)} \\ \text{Neutral} & \text{Otherwise} \end{cases}$$

$$\text{where } v = \frac{(s_W^2/n(W) + s_w^2/n(w))^2}{\frac{(s_W^2/n(W))^2}{n(W)-1} + \frac{(s_w^2/n(w))^2}{n(w)-1}}$$

# Corpus-based Approaches

Hur et al. (2016)

- Building Up a Sentiment Dictionary based on Movie Review Data

## ✓ Example

Collocation	Avg	Stdev.	Count	NMovies	T	t-dist	Diag
멋지/vv	9.52	1.22	1,617	341	61.88	1.96	Positive
실망/NNG_시키/XSV_지/ECD_않/VXV	9.68	0.97	829	260	60.87	1.96	Positive
재밌/VA_게/ECD_보/VXV	9.13	1.70	4,679	565	59.90	1.96	Positive
재미/NNG_잇/VV	9.57	1.45	2,004	379	59.74	1.96	Positive
깔끔/XR_하/XSA	9.24	1.22	1,336	358	48.02	1.96	Positive
잘/MAG_만들/VV_ㄴ/ETD_영화/NNG	9.26	1.49	1,903	342	47.47	1.96	Positive
못/MAG_보시/VV_는/ETD_분/NNG	7.83	2.37	12	9	0.29	2.2	Neutral
남자/NNG_둘/NNG	7.78	3.18	36	34	0.26	2.03	Neutral
영웅/NNG_이야기/NNG	7.71	2.76	48	24	0.18	2.01	Neutral
복수극/NNG	7.68	2.75	104	38	0.17	1.98	Neutral
코믹/NNG_성/XSN	7.7	2.83	44	31	0.16	2.02	Neutral
도저히/MAG_모르/VV	4.27	3.28	15	15	-3.99	2.14	Negative
손발/NNG_오글거리/VV	4.41	3.8	22	18	-3.99	2.08	Negative
무리수/NNG	5.62	3.11	39	25	-4.06	2.02	Negative
안타깝/VA_ㄴ/ETD_영화/NNG	6.42	3.21	119	84	-4.13	1.98	Negative
좀/MAG_지겹·VA	6.62	2.2	89	72	-4.38	1.99	Negative
여지/NNG_oir/VCP	6.3	2.96	121	88	-4.98	1.98	Negative

# AGENDA

01 Overview

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02 Architecture

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03 Lexicon-based Approach

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04 Machine Learning-based Approach

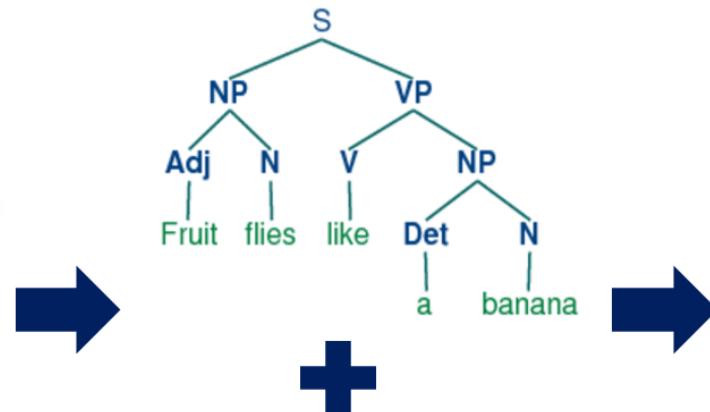
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# Machine Learning-based Approach

조수현 외 (2016)

- Regression-based Approach

- TripAdvisor 사이트에서 서울 여행지에 대한 평가 댓 글과 5점 척도의 평점 수집(21620개)
- 형태소 분석(POS tagging)을 통해 형용사, 동사, 명사 추출
- Lemmatization을 실시하여 문서 단어 행렬(document term matrix) 구성
- 문서 단어 행렬을 사전에 정의한 서울의 관광지 유형에 따라 분류



Crawling을 통한 데이터 수집

POS tagging + Lemmatization

유형	문서 수	장소
명소&랜드마크	14,443	남산, 경복궁, 인사동 등
쇼핑&시장	3,589	명동쇼핑거리, 코엑스, 광장시장 등
박물관&전시관	3,588	전쟁기념관, 국립 민속박물관 등

유형 별 관광지, 문서의 수

	Term1	Term2	...	Term(m)
Doc1	1	0	...	7
Doc2	0	0	...	0
...	...	...	...	...
Doc(n)	2	0	...	2

Document term matrix

# Machine Learning-based Approach

조수현 외 (2016)

- Regression-based Approach

- 유형별 관광지의 document term matrix에서 각 유형별로 벌점화 회귀분석을 활용하여 감정사전 구축
- 10-fold cross validation을 적용하여 엘라스틱 넷 학습
- Validation data에 대해 여러 지표를 이용하여 성능을 비교한 결과 감정사전으로서 타당한 성능확보



	명소&랜드마크	쇼핑&시장	박물관&전시관
어휘	awesome fantastic prime yummy souvenir favourite beautiful gorgeous inexpensive confuse ugly overpriced dirty waste terrible disappoint pity bore humid expensive worse	great helpful excellent heaven love amaze wonderful yummy wanna fantastic overcrowd 	awesome fantastic reminder incredible amaze heritage magnificent perfect interactive trouble small bore poor queue lack warn tiny crowd
Elastic net	2,826	1,319	1,329

유형 별 관광지의 감정사전 어휘개수

	명소&랜드마크	쇼핑&시장	박물관&전시관
ACC	0.8246	0.7465	0.8717
REC	0.8911	0.8028	0.9451
PRE	0.8999	0.8686	0.9149
BCR	0.6444	0.6506	0.4561
MAE	0.5727	0.6446	0.5625
COR	0.4434	0.3887	0.3575

유형 별 관광지의 감정사전 성능

# Machine Learning-based Approach

조수현 외 (2016)

- Regression-based Approach

- ✓ Elastic Net

- Response variable: rating of a review
    - Explanatory variables: words used in the review
    - Use the regression coefficient as the sentiment score of the corresponding word

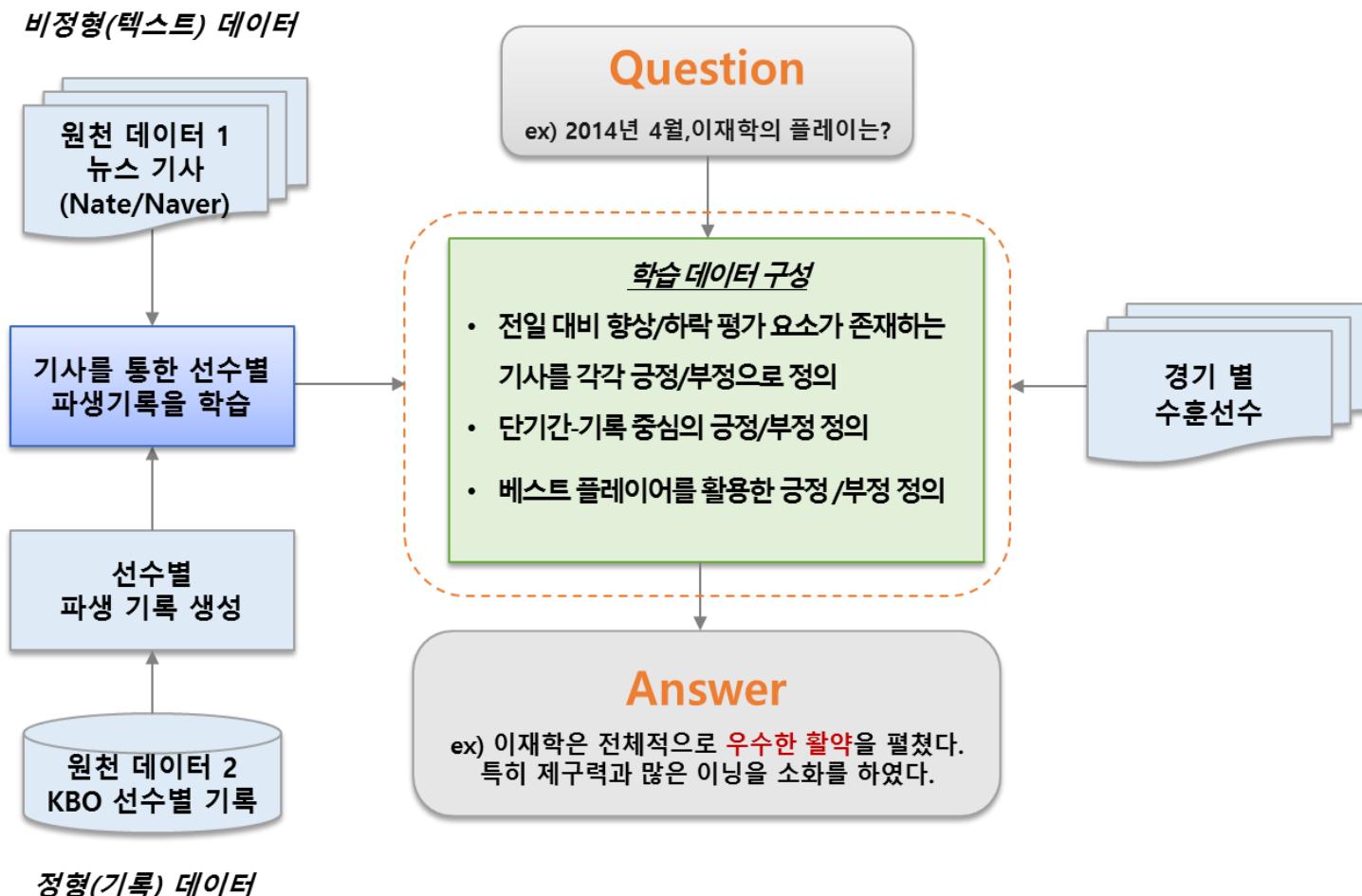
$$\hat{\beta} = \arg \min_{\beta} \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda_2 \|\beta\|^2 + \lambda_1 \|\beta\|_1$$

- The  $\ell_1$  part of the penalty generates a sparse model.
    - The quadratic part of the penalty
      - Removes the limitation on the number of selected variables;
      - Encourages *grouping effect*;
      - Stabilizes the  $\ell_1$  regularization path.

# Machine Learning-based Approach

Park et al. (2016+)

- Neural Network-based Approach
  - ✓ Evaluating a player based on the sentiment of news articles



# Machine Learning-based Approach

Park et al. (2016+)

## • Neural Network-based Approach

- ✓ Evaluating a player based on the sentiment of news articles

### Best Player Case



테임조 첫 그랜드슬램 폭발, 시즌 11호 홈런

OSEN | 2014.05.29. 네이버뉴스

NC 외국인 타자 에릭 테임조가 첫 만루 홈런을 쏘아올렸다. 테임조는 29일 대전구장에서 열린 2014 한국야쿠르트 세븐 프로야구 한화와 원정경기에 5번타자 1루수로 선발출장, 5-3으로 리드한 4회 2사 만루에서...

<2014.05.29 NC 테임조 관련기사>

날짜	선수	타수	안타	타점	득점	타율	홈런	볼넷	삼진
05-28	테임조	3	2	0	2	0.315	0	1	0
볼넷 비율	삼진 비율	볼/삼 비율	출루율	장타율	ops	ISO	타석당 홈런	RC	BABIP
0.33	0	Inf	0.75	1.00	1.75	0.68	0	2.25	0.67



날짜	선수	타수	안타	타점	득점	타율	홈런	볼넷	삼진
05-29	테임조	6	5	7	4	0.333	2	0	0
볼넷 비율	삼진 비율	볼/삼 비율	출루율	장타율	ops	ISO	타석당 홈런	RC	BABIP
0	0	NA	0.83	2.00	2.83	1.67	0.333	10.00	0.75



타수	안타	타점	득점	타율	홈런	타율	홈런	출루율	장타율	ops	ISO	타석당 홈런	RC	BABIP
+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0



Best player

1

### Non-best Player Case



'프로 12년차' 손시현, 통산 1000경기 출장 눈앞

파이낸셜뉴스 | 2014.05.29. 네이버뉴스

손시현(34,NC)이 통산 1,000경기 출장을 눈앞에 뒀다. 지난 2003년 두산에서 선수생활을 시작한 손시현은 군 입대로 인해 자리를 비운 2007년과 2008년을 제외하고 지난해까지 두산에서 뛰었다. 두산 유니폼을 입는...

<2014.05.29 NC 손시현 관련기사>

날짜	선수	타수	안타	타점	득점	타율	홈런	볼넷	삼진
05-28	손시현	4	1	0	0	0.292	0	0	0
볼넷 비율	삼진 비율	볼/삼 비율	출루율	장타율	ops	ISO	타석당 홈런	RC	BABIP
0	0	0	0.25	0.25	0.5	-0.042	0	0.25	0.25



날짜	선수	타수	안타	타점	득점	타율	홈런	볼넷	삼진
05-29	손시현	4	1	0	1	0.291	0	1	0
볼넷 비율	삼진 비율	볼/삼 비율	출루율	장타율	ops	ISO	타석당 홈런	RC	BABIP
0.25	0	Inf	0.4	0.25	0.65	-0.041	0	0.40	0.25

이전  
경기기록

당일  
경기기록

Target

득점	볼넷	볼넷 비율	출루율	ops	ISO	타석당 홈런	RC	BABIP
+1	+1	+1	+1	+1	+1	+1	+1	+1
0	0	0	0	0	0	0	0	0



Best player

0

# Machine Learning-based Approach

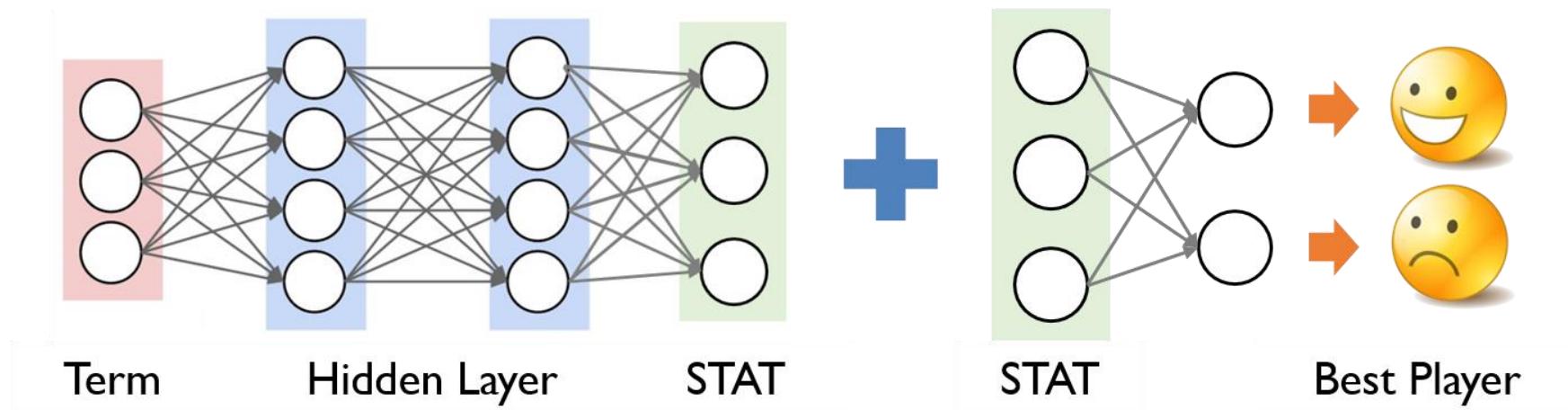
Park et al. (2016+)

- Neural Network-based Approach

- ✓ Evaluating a player based on the sentiment of news articles

<문장을 벡터화하여 기록의 변화를 학습하는 모델>

<기록 변화를 통해 우수 선수를 학습하는 모델>



투수의 경우

9,670 terms    9670 : 4000 : 2000 : 1000 : 18    STAT 18개    18 : 2    우수 / 비우수

타자의 경우

8,686 terms    8686 : 4000 : 2000 : 1000 : 9    STAT 9개    9 : 2    우수 / 비우수

# Machine Learning-based Approach

Park et al. (2016+)

- Neural Network-based Approach

- ✓ Evaluating a player based on the sentiment of news articles

Player	Line	Score	승	패배	피안타	피홈런	볼넷	실점	평균 자책점	이닝당 삼진	이닝당 볼넷	삼진 /볼넷	방어율
웨버	NC웨버는 70이닝 동안 1안타 3볼넷 10탈삼진으로 무실점 호투했다.	0.991	1	0	0	0	1	0	0	1	1	1	0
이재학	이재학 '10승', 3년만에 달라진 위상 증명하다	0.986	1	0	0	1	0	1	0	0	0	1	0
이태양	'이태양 완벽투' NC LG 상대로 창단 첫 스윕	0.966	1	0	0	0	0	0	0	0	0	1	0
에릭	한편, 이날 70이닝 3실점으로 잘 던지며 7경기 만에 국내 첫 승을 거둔 에릭은 "굉장히 훌륭된다."	0.803	1	0	1	0	0	0	0	0	0	0	0
찰리	어이없는 실책 2개가 나오자 찰리는 흔들리기 시작했다.	0.506	0	1	1	1	0	1	0	1	0	1	1
찰리	찰리가 대량 실점을 했지만 그 과정에서 3루수 모창민과 1루수 테임즈의 실책이 동반되면서 자책은 1점 밖에 되지 않았다.	0.506	0	1	1	1	0	1	0	1	0	1	1
원종현	NC 원종현이 패전투수가 됐다.	0.293	0	1	0	0	0	1	1	1	0	1	1
원종현	세 번째 투수로 등판한 원종현 역시 1사후 8번 김성현에게 솔로포를 맞았다.	0.102	0	0	0	1	1	0	1	1	1	0	0
이재학	NC 선발 이재학은 80이닝 8피안타(2홈런) 5탈삼진 3볼넷 2실점을 기록했다.	0.079	0	0	1	1	0	1	1	0	0	0	1
이혜천	이혜천이 올라온 뒤 한꺼번에 5점을 내주면서 맥빠진 경기가 되고 말았다.	0.066	0	0	1	1	0	1	0	0	1	0	0

# Machine Learning-based Approach

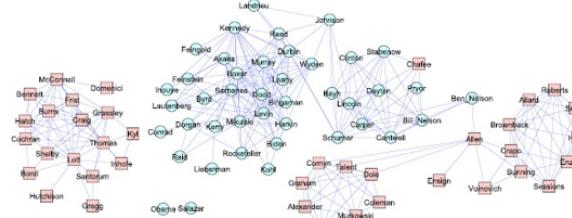
서덕성 외 (2016)

- Semi-supervised Learning-based Approach

## ❖ Framework

Text + scaled score  
데이터 수집

02



임베딩 공간에서 거리기반  
네트워크 구축

04

추정한 감성 점수  
성능 평가

🔍 데이터 준비



Word2Vec



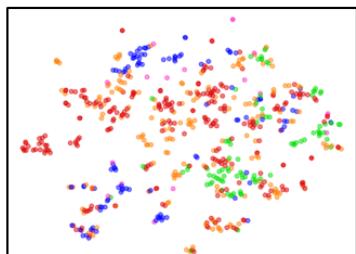
Construct  
network

↑↓ Graph based  
SSL

✓ 성능 평가

01

고차원으로 표현된 단어를  
저차원으로 임베딩



03

명백한 label을 미리 선정/할당  
label propagation을 이용  
score 추정

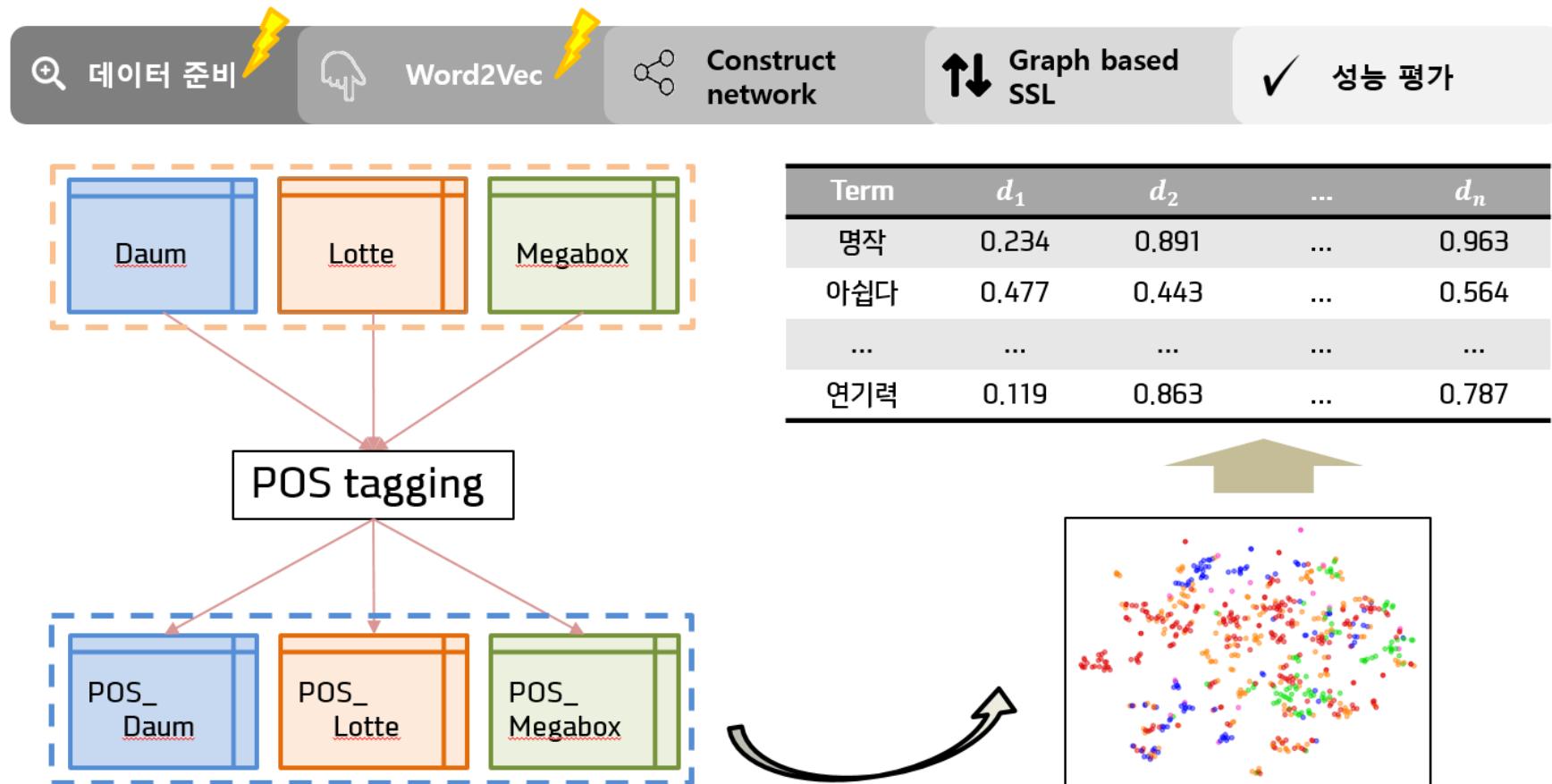
Term	Score
재미있다	1
...	...
지루하다	-1

05

# Machine Learning-based Approach

서덕성 외 (2016)

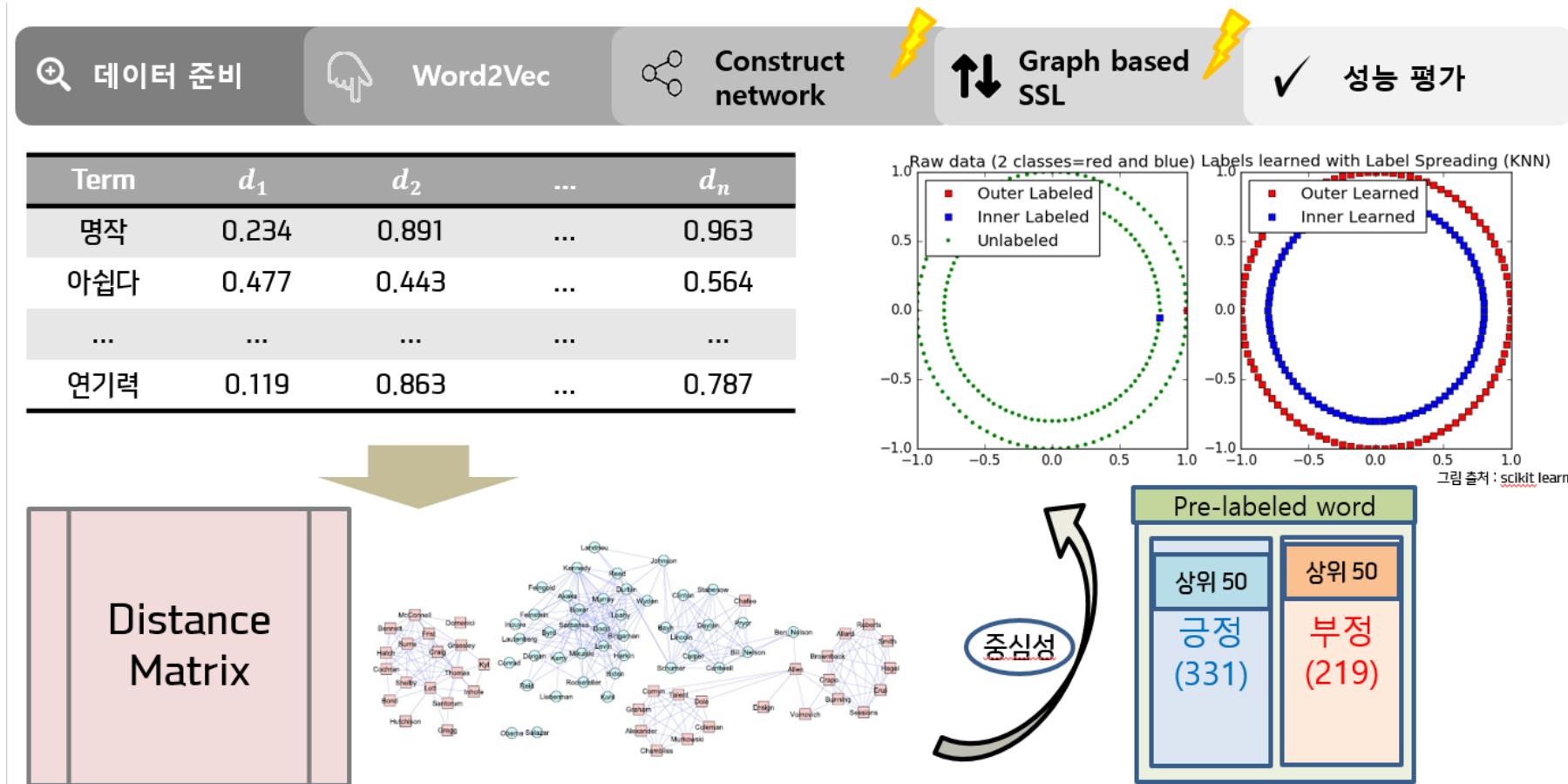
- Semi-supervised Learning-based Approach



# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach



# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach

- ✓ Pre-labeled sentiment words

긍정		
좋다	역시	연기력
훌륭하다	즐겁다	아름답다
재밌다	기대하다	긴장감
사랑	좋아하다	매력
재미있다	멋지다	짱
감동	대박	빠지다
기대	웃다	멋있다
최고	눈물	울다
재미	추천	코믹
괜찮다	슬프다	오랜만

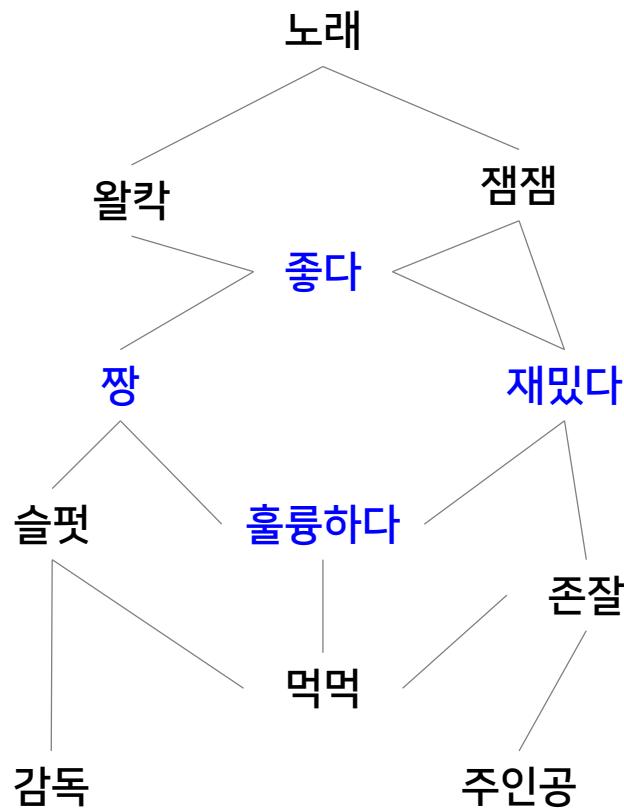
부정		
억지	지루	때우다
아쉬움	약하다	부담
절대	흠	부끄럽다
짜증	진부	고통
지루함	싫다	난해
밉다	별루	거슬리다
이상하다	심하다	망치다
킬링타임	식상하다	애매
필요없다	까다	거지
어이	졸리다	질질

# Machine Learning-based Approach

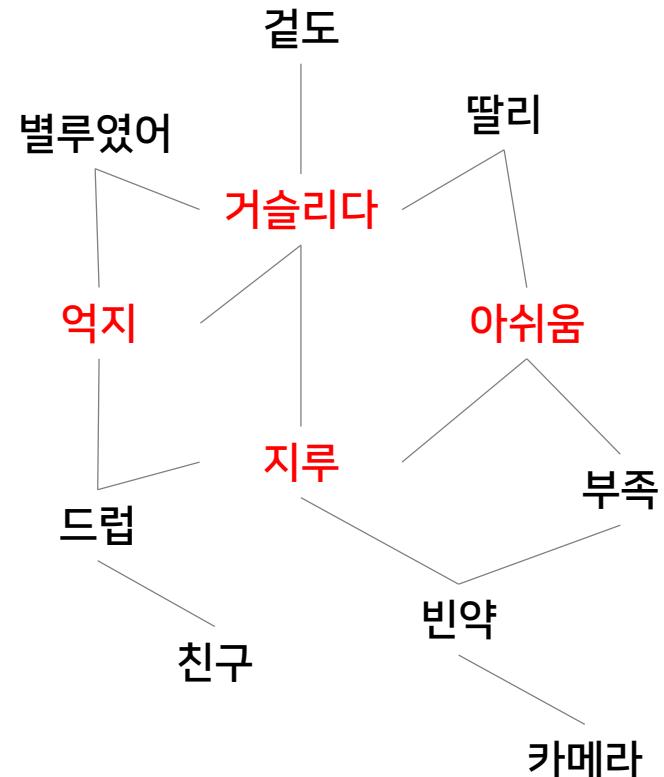
서덕성 외 (2016)

- Semi-supervised Learning-based Approach

- ✓ An illustrative example of label propagation/spreading



보다

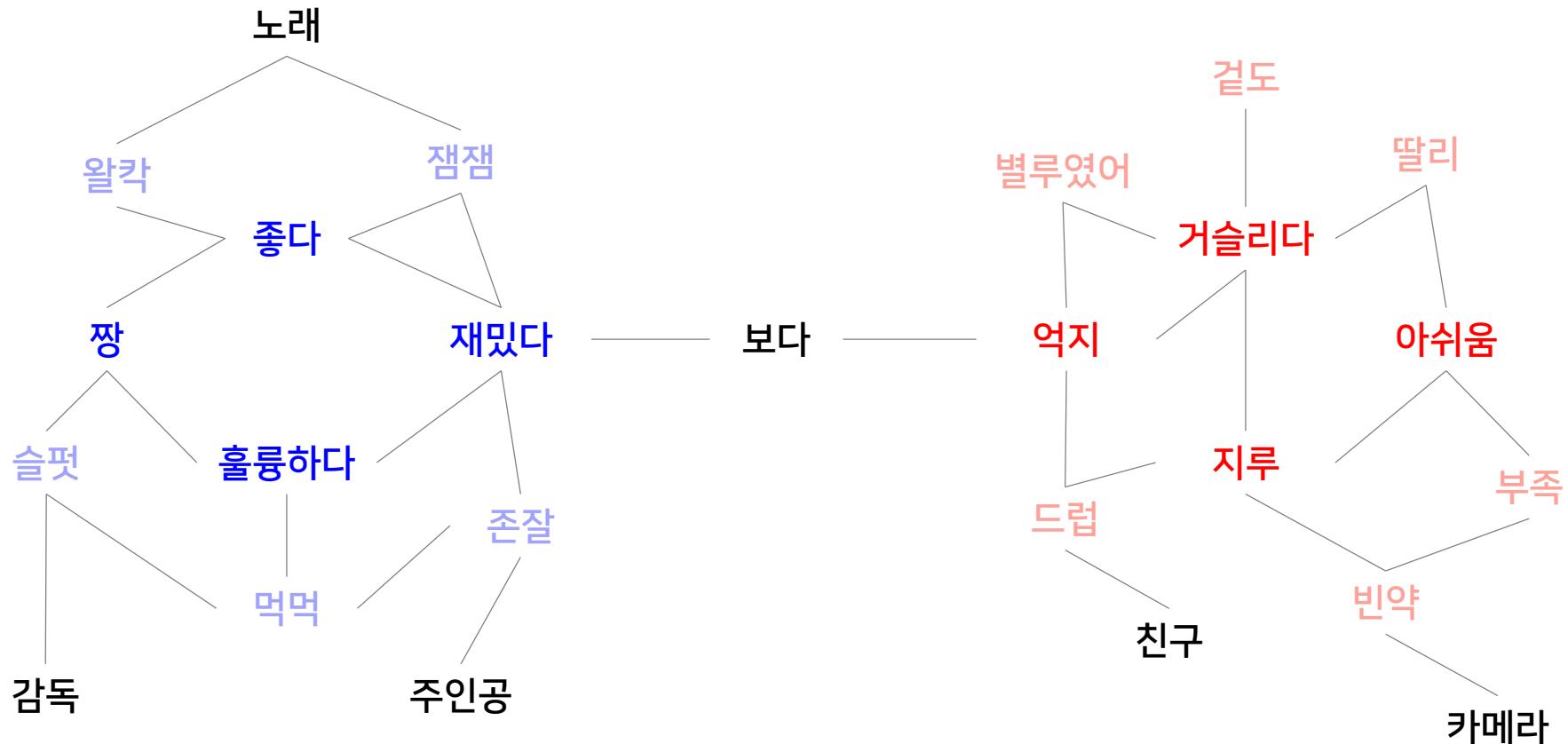


# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach

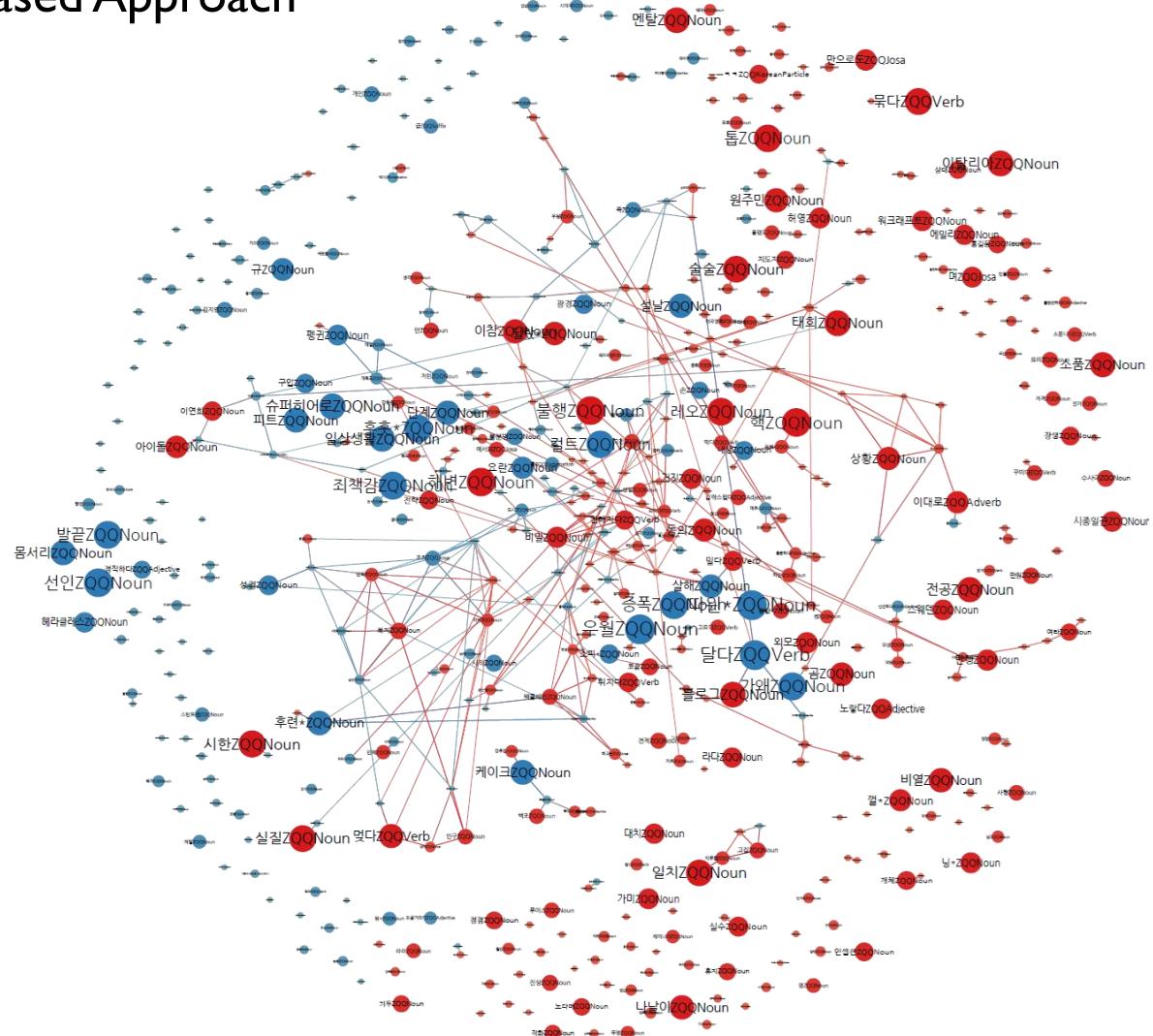
- ✓ An illustrative example of label propagation/spreading



# Machine Learning-based Approach

서덕성 외 (2016)

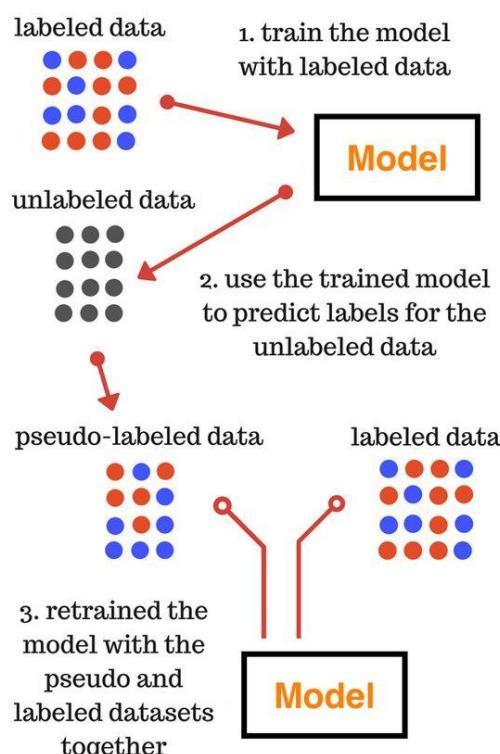
- Semi-supervised Learning-based Approach



# Machine Learning-based Approach

- Self-Training

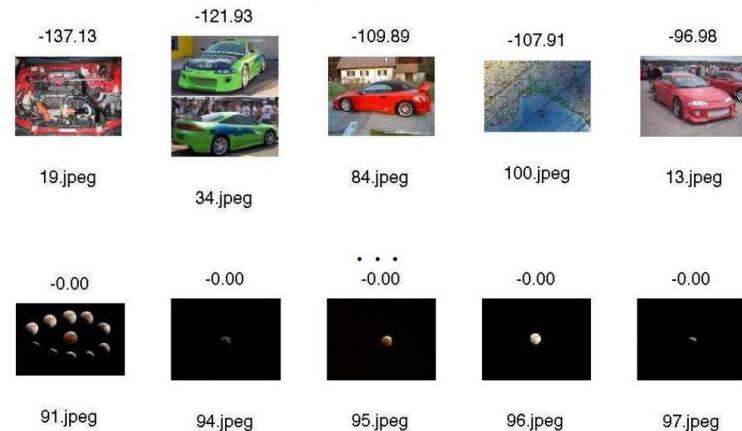
- ✓ 정답이 있는 어휘들만을 사용해서 긍정/부정 분류기 학습
- ✓ 정답이 없는 어휘들에 분류기를 적용하여 결과의 신뢰도가 높으면 정답으로 지정 후 분류기 재학습



1. Train a naïve Bayes classifier on the two initial labeled images



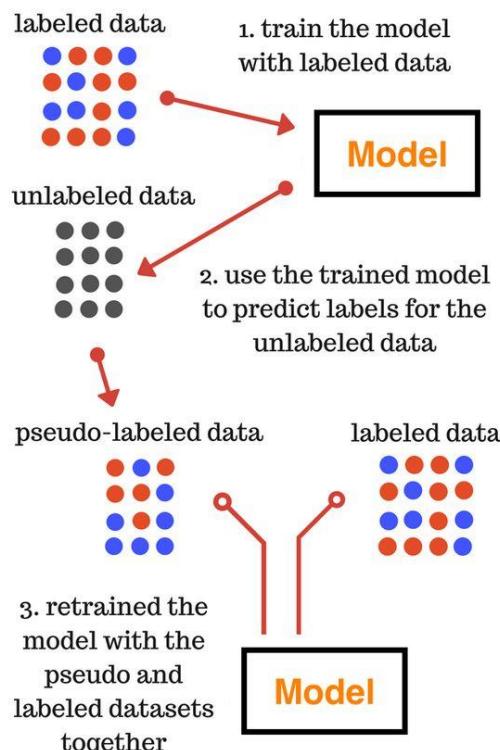
2. Classify unlabeled data, sort by confidence  $\log p(y = \text{astronomy} | x)$



# Machine Learning-based Approach

- Self-Training

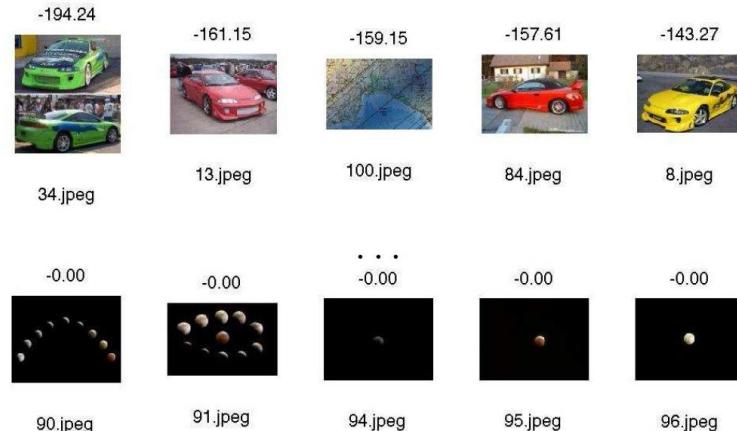
- ✓ 정답이 있는 어휘들만을 사용해서 긍정/부정 분류기 학습
- ✓ 정답이 없는 어휘들에 분류기를 적용하여 결과의 신뢰도가 높으면 정답으로 지정 후 분류기 재학습



3. Add the most confident images and **predicted** labels to labeled data



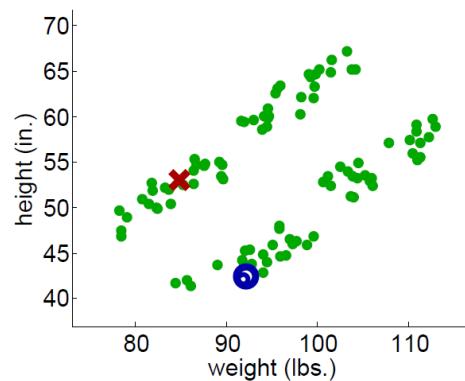
4. Re-train the classifier and repeat



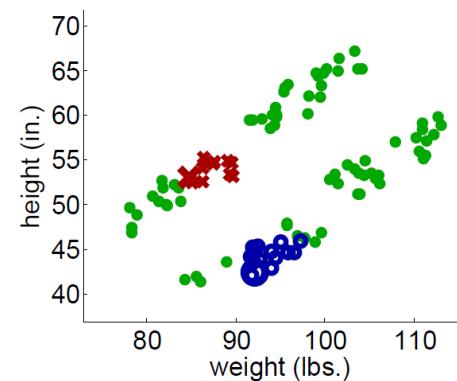
# Machine Learning-based Approach

- Self-Training

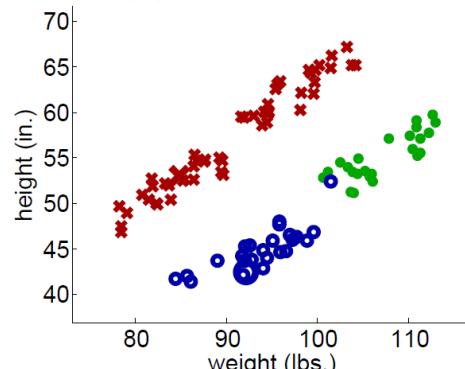
- ✓ 정답이 있는 어휘들만을 사용해서 긍정/부정 분류기 학습
- ✓ 정답이 없는 어휘들에 분류기를 적용하여 결과의 신뢰도가 높으면 정답으로 지정 후 분류기 재학습



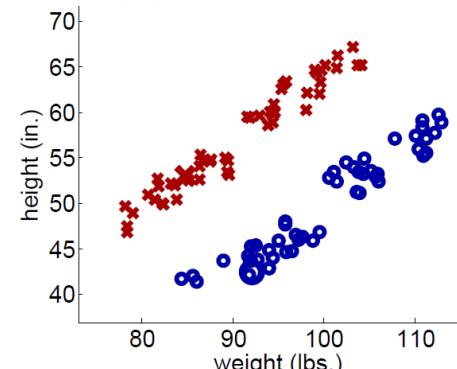
(a) Iteration 1



(b) Iteration 25



(c) Iteration 74



(d) Final labeling of all instances

# Machine Learning-based Approach

- Self-Training

- ✓ An illustrative example of self-training

노래

곁도

왈칵

잼잼

별루였어

딸리

좋다

거슬리다

짱

재밌다

보다

억지

아쉬움

슬펐

훌륭하다

지루

부족

존잘

드립

먹먹

빈약

감독

주인공

친구

카메라

# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach

- ✓ Pre-labeled words

Positive pre-labeled words			Negative pre-labeled words		
좋다	역시	연기력	억지	지루	때우다
훌륭하다	즐겁다	아름답다	아쉬움	약하다	부담
재밌다	기대하다	긴장감	절대	흠	부끄럽다
사랑	좋아하다	매력	짜증	진부	고통
재미있다	멋지다	짱	지루함	싫다	난해
감동	대박	빠지다	밉다	별루	거슬리다
기대	웃다	멋있다	이상하다	심하다	망치다
최고	눈물	울다	킬링타임	식상하다	애매
재미	추천	코믹	필요없다	꺄다	거지
괜찮다	슬프다	오랜만	어이	졸리다	질질

# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach

- ✓ Sentiment scores for unlabeled words

Positive		Negative	
Words	Sentiment Score	Words	Sentiment Score
슬펐	1	딸리	-0.9576
먹먹	1	별루였어	-0.5458
이뿌	0.8282	걸도	-0.4673
괜찮	0.5956	드립	-0.4140
잼잼	0.5126	부족	-0.3713
신나요	0.4357	심해	-0.3449
눈시울	0.4089	어설퍼	-0.3123
짱	0.4002	미흡	-0.3062
왈칵	0.4001	지루	-0.2728
존잘	0.3851	빈약	-0.2531

# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach

- ✓ Performance evaluation (Word sentiment)

	ACC	REC	PRE	F1	BCR
Proposed method	0.9311	0.9288	0.9596	0.9439	0.9319
Lasso regression	0.4909	0.3807	0.6269	0.4737	0.5003

- ✓ Performance evaluation (Review polarity)

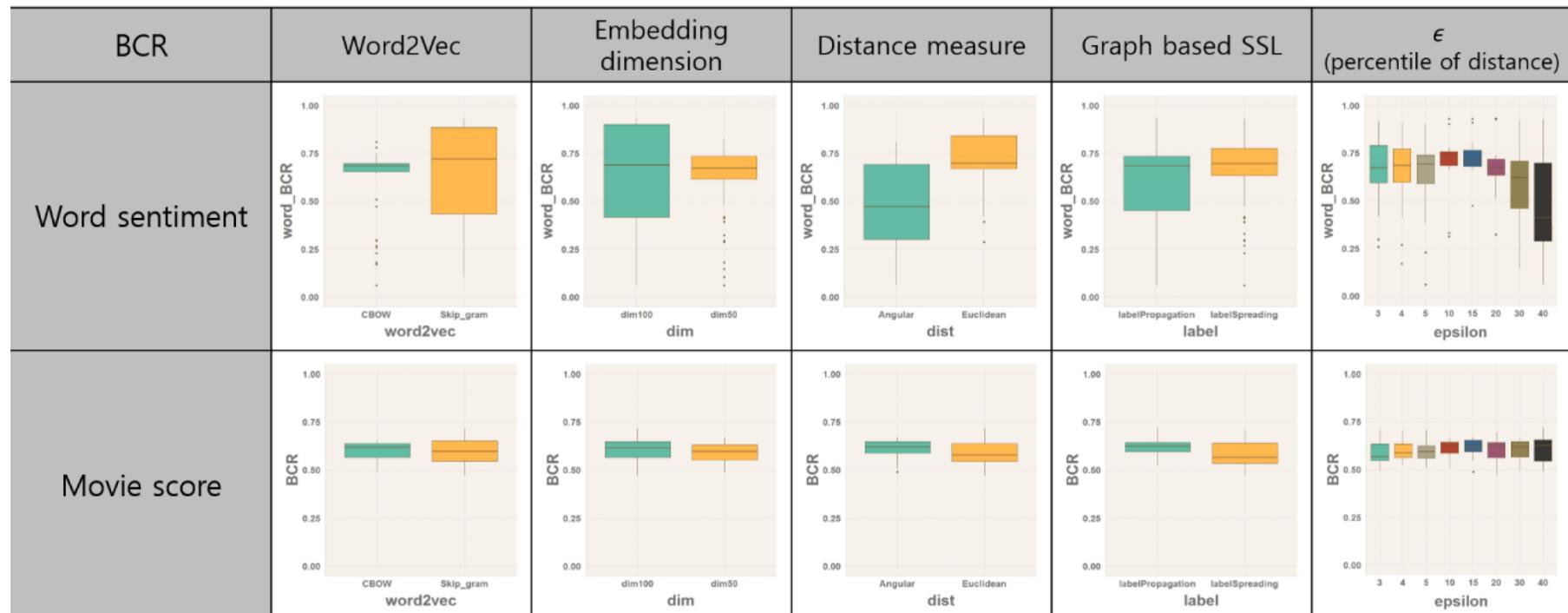
	ACC	REC	PRE	F1	BCR
Proposed method	0.7832	0.8163	0.9113	0.8612	0.7162
Lasso regression	0.7045	0.7704	0.8778	0.8206	0.4234

# Machine Learning-based Approach

서덕성 외 (2016)

- Semi-supervised Learning-based Approach

✓ Parameter sensitivity



# Machine Learning-based Approach

- 뉴스 텍스트 감성 분석 절차

- ✓ 1단계: Label spreading 또는 Self-Training 기법을 활용하여 감성 점수를 산출
- ✓ 2단계: 각 기사별로 감성 점수가 등장하는 Unique 어휘 수 계산
- ✓ 3단계: 등장 어휘 수가 더 많은 범주로 기사를 할당

- 예시 (실제 어휘 점수와는 상관 없음, 이해를 위해 생성한 예시임)

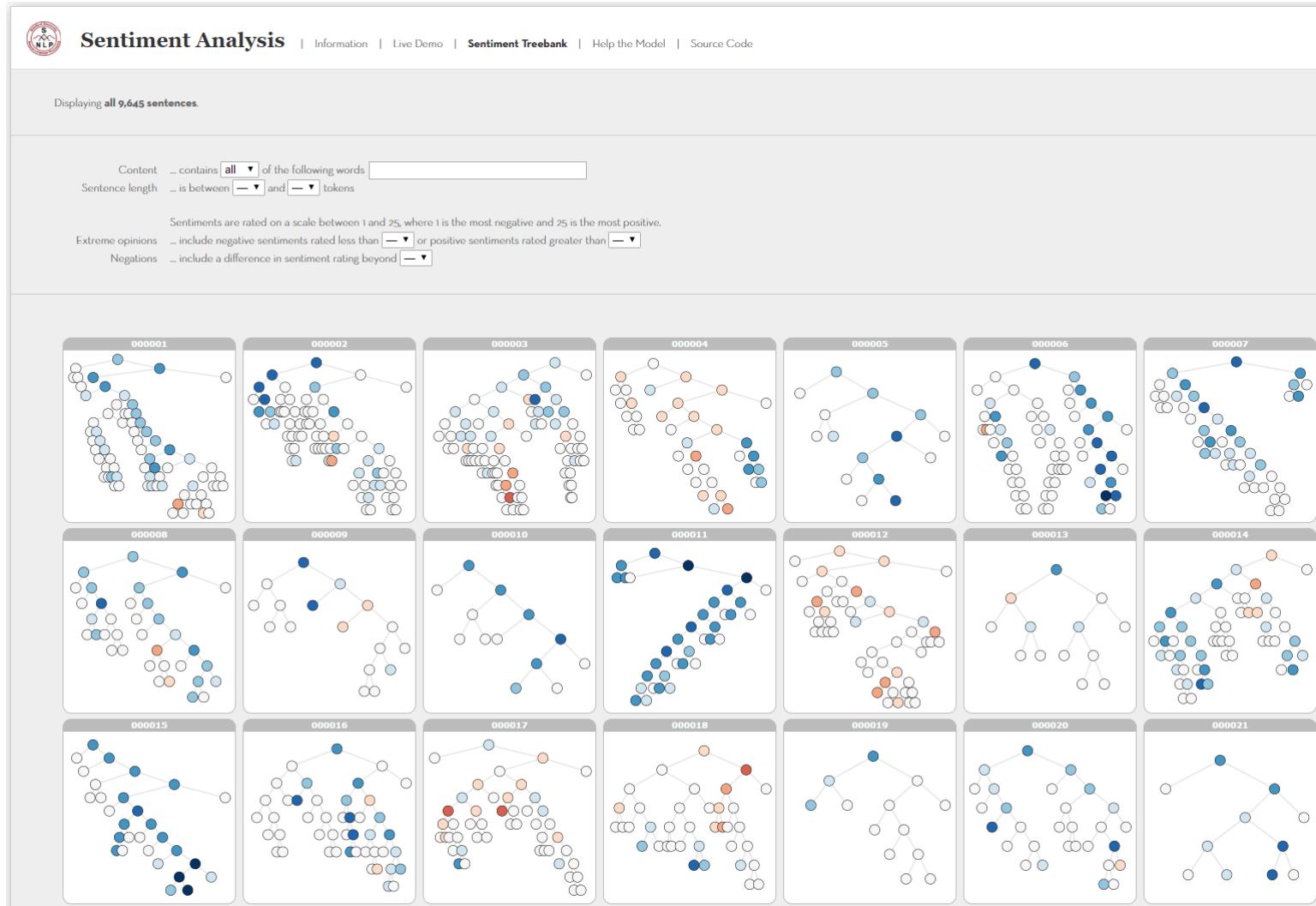
패스트트랙 의결을 하루 앞둔 24일 국회는 극렬 대치를 넘어 '막장'으로 치달았다.  
국회에서 타협의 정치가 사라진 자리엔 몸싸움과 고성, 막말만 남았다.  
이날 국회는 오전부터 과거 몸싸움을 벌이던 '동물 국회'의 장면이 연출하는가 하면, 이 과정에서 국회를  
대표하는 국회의장은 병원 신세를 져야 했다. 여기에 제 1야당 자유한국당은 대치 과정에서 신체접촉을 한 문희상  
의장이 성추행을 했다며 강력 반발하기도 했다.  
또 한국당 나경원과 바른미래당 김관영 원내대표는 서로에게 폭로, 막말 성 발언을 주고 받으며 설전을 벌이는  
또 다른 싸움이 펼쳐졌다. 두 야당 원내 사령탑이 서로 치고 받은 날선 '신경전' 펼친 것이다.

- ✓ 긍정 어휘: 타협 (1개)
- ✓ 부정 어휘: 국회, 극렬, 대치, 막장, 치달, 몸싸움, 고성, 막말, 싸움, 성추행, 강력, 반발, 폭로,  
설전, 신경전 (15개)
- ✓ 이 기사는 부정 (긍정 어휘 1개 < 부정 어휘 15개)으로 판별

# Machine Learning-based Approach

Socher et al. (2013)

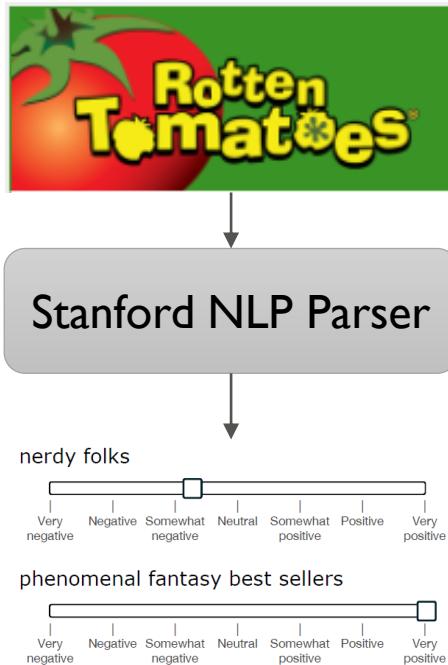
- Recursive Neural Tensor Network (RNTN)



# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN): Sentiment Treebank
  - ✓ Fully labeled parse trees that allows for a complete analysis of the compositional effects of sentiment in languages

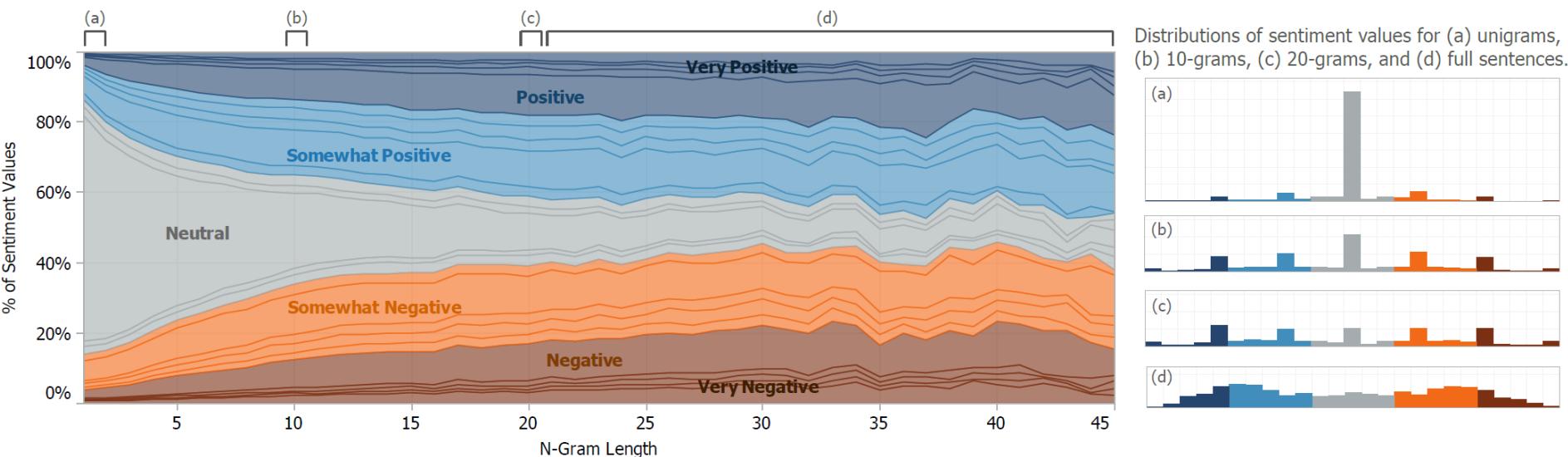


- 10,662 sentences
- 1,100 cases are split into multiple sentences
- 11,855 sentences with 215,154 phrases
- Label all phrases using Amazon Mechanical Turk
- Slider has 25 different values
- Each phrase is annotated by 3 human judges

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN): Sentiment Treebank

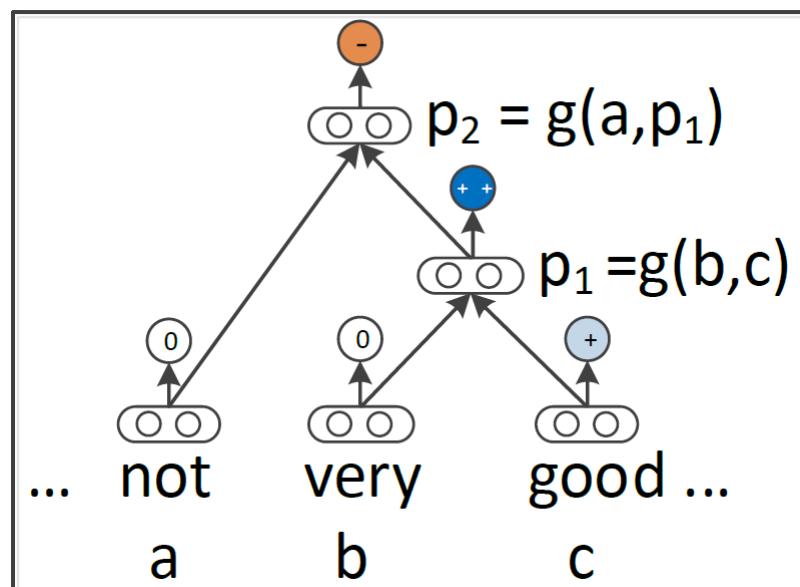


- ✓ Majority of shorter phrases are neutral
- ✓ Stronger sentiment often builds up in longer phrases
- ✓ Main experiment is to recover the five labels for phrases of all lengths

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)
  - ✓ Benchmark Model I: Recursive Neural Models



- Each word is represented as a d-dimensional vector
- Posterior probability over labels given the word vector:

$$y^{word} = \text{softmax}(W_s \cdot word)$$

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)

- ✓ Benchmark Model I: Recursive Neural Models

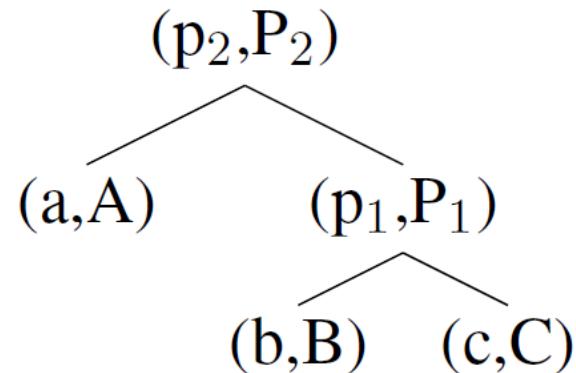
$$p_1 = f\left(W \begin{bmatrix} b \\ c \end{bmatrix}\right), \quad p_2 = f\left(W \begin{bmatrix} a \\ p_1 \end{bmatrix}\right)$$

- $f = \tanh$  is a standard element-wise nonlinearity
- Parent vectors must be of the same dimensionality to be recursively compatible and be used as input to the next composition
- Each parent vector is given to the same softmax classifier to compute its label probabilities

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)
  - ✓ Benchmark Model 2: Matrix-Vector RNN (MV-RNN)
    - Limitations of the standard RNN: Most of the parameters are associated with words and each composition function that computes vectors for longer phrases depends on the actual words being combined



$$p_1 = f\left(W \begin{bmatrix} Cb \\ Bc \end{bmatrix}\right), \quad P_1 = f\left(W_M \begin{bmatrix} B \\ C \end{bmatrix}\right)$$

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)

- ✓ Limitation of the MV-RNN: **the number of parameters becomes very large and depends on the size of the vocabulary**

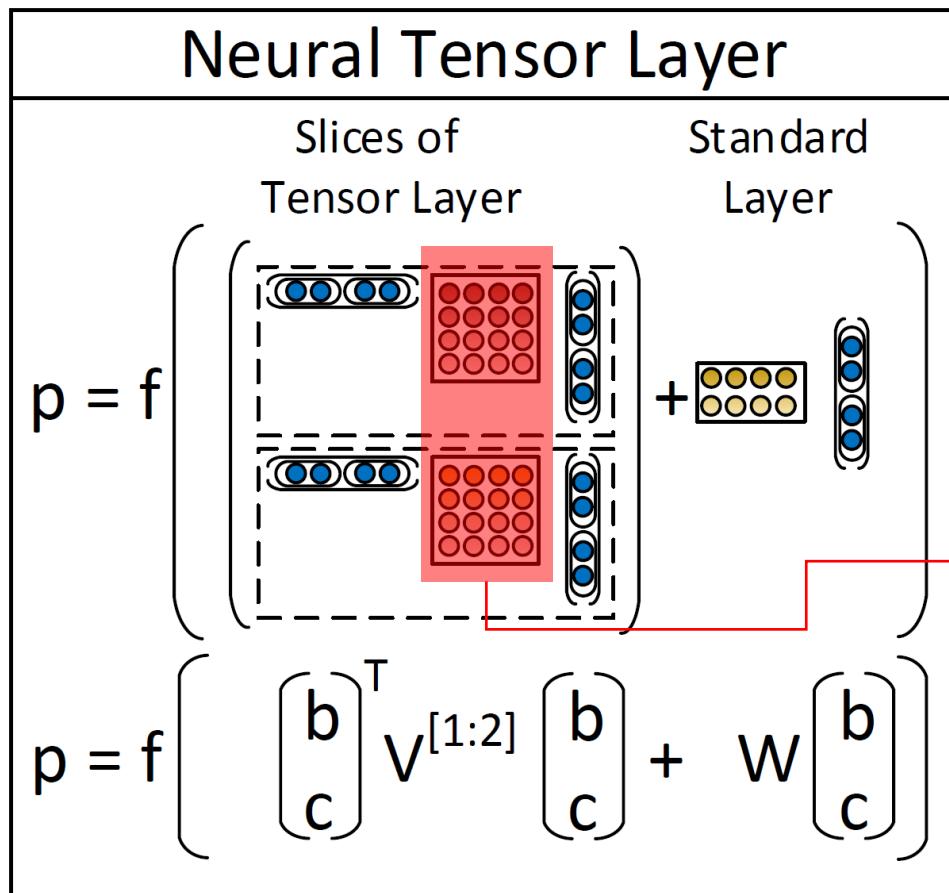
	Standard RNN	MV-RNN	RNTN
Word vector	$d \times  V $	$d \times  V $	$d \times  V $
Softmax	$C \times d$	$C \times d$	$C \times d$
Composition	$d \times 2d$	$W : d \times 2d$ $W_M : d \times 2d$	$W : d \times 2d$ $V^{[1:d]} : 2d \times 2d \times d$



# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)



$$p_1 = f \left( \left[ \begin{array}{c} b \\ c \end{array} \right]^T V^{[1:d]} \left[ \begin{array}{c} b \\ c \end{array} \right] + W \left[ \begin{array}{c} b \\ c \end{array} \right] \right)$$

$$p_2 = f \left( \left[ \begin{array}{c} a \\ p_1 \end{array} \right]^T V^{[1:d]} \left[ \begin{array}{c} a \\ p_1 \end{array} \right] + W \left[ \begin{array}{c} a \\ p_1 \end{array} \right] \right)$$

Each slice of the tensor can capture a specific type of composition

$$E(\theta) = \sum_i \sum_j t_j^i \log y_j^i + \lambda \|\theta\|^2$$

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)

## ✓ Experiments

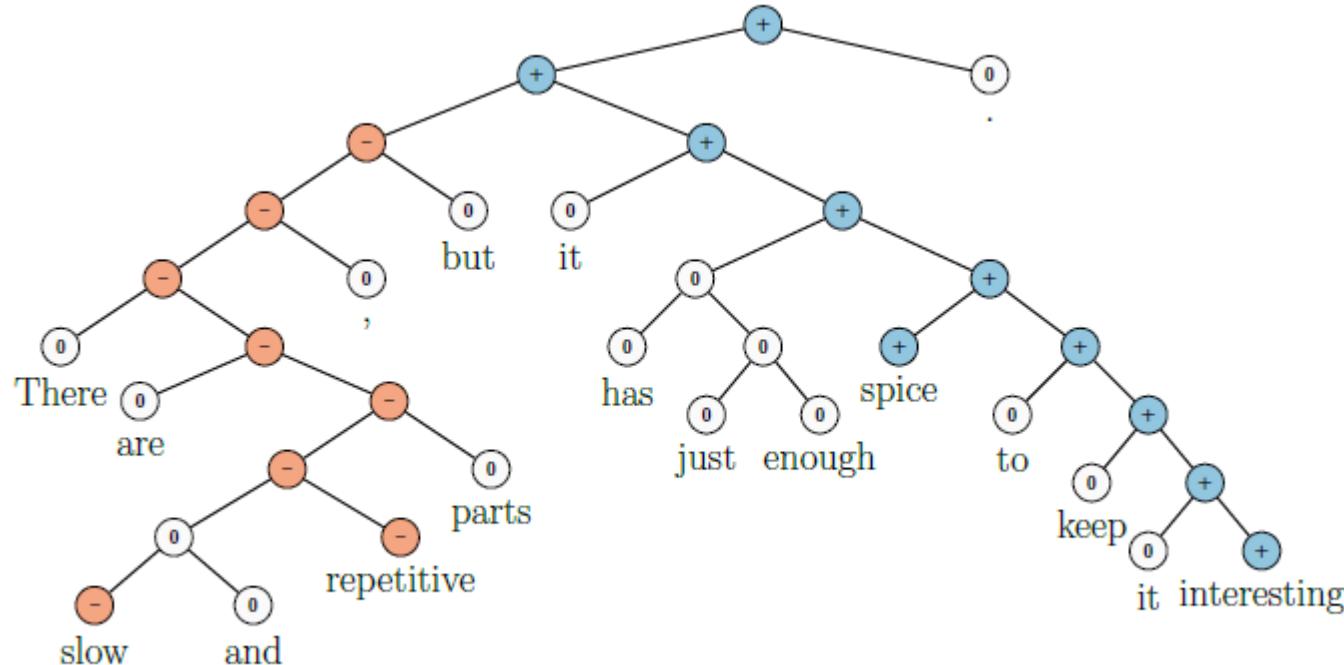
Model	Fine-grained		Positive/Negative	
	All	Root	All	Root
NB	67.2	41.0	82.6	81.8
SVM	64.3	40.7	84.6	79.4
BiNB	71.0	41.9	82.7	83.1
VecAvg	73.3	32.7	85.1	80.1
RNN	79.0	43.2	86.1	82.4
MV-RNN	78.7	44.4	86.8	82.9
RNTN	<b>80.7</b>	<b>45.7</b>	<b>87.6</b>	<b>85.4</b>

- Optimization performance for all models was achieved at word vector sizes between 25 and 35

# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)
  - ✓ Model Analysis: Contrastive Conjunction: X but Y (131 cases)
    - RNTN: 41%, MV-RNN: 37%, RNNL 36%, biNB: 27%



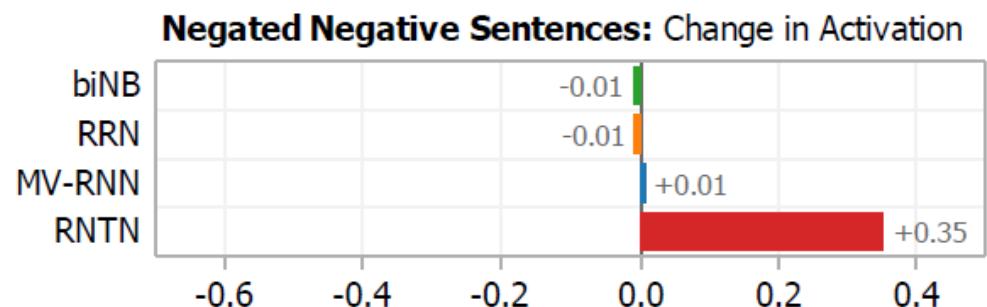
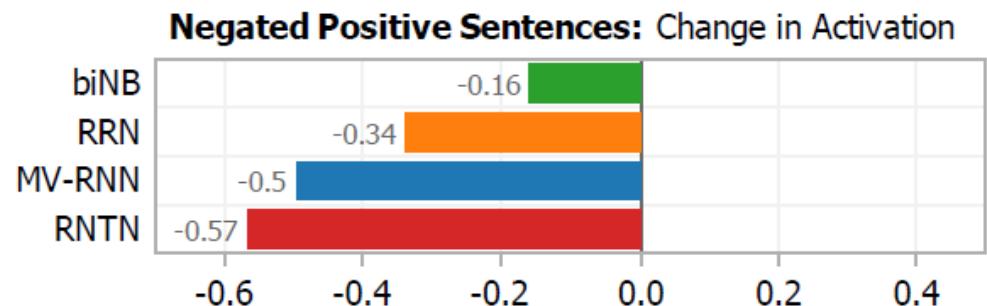
# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)

- ✓ Model Analysis: High Level Negation

Model	Accuracy	
	Negated Positive	Negated Negative
biNB	19.0	27.3
RNN	33.3	45.5
MV-RNN	52.4	54.6
RNTN	<b>71.4</b>	<b>81.8</b>



# Machine Learning-based Approach

Socher et al. (2013)

- Recursive Neural Tensor Network (RNTN)

- ✓ Model Analysis: Most positive and negative phrases

$n$	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



ANY  
questions?

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