Semantic Analysis:
General Sentiment Scoring

Natural Language Processing

General Sentiment Scoring

The "table stakes" version of sentiment analysis is a simple two-dimensional detection of general negative or positive sentiment.

General Sentiment Scoring

Usually scored from -1 to 1 (“polarity”)

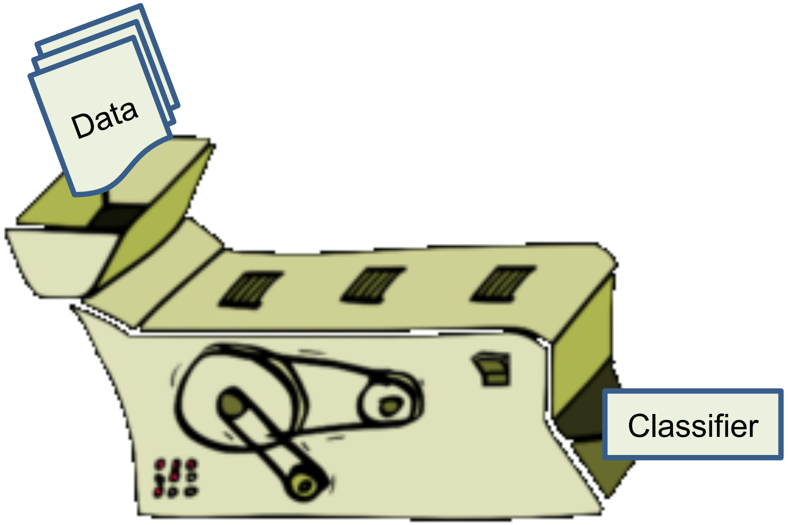
- Occasionally scored somewhat differently, e.g., from -4 to 4 or even from -∞ to ∞

0 represents either

- neutral sentiment, or
- nondetection of sentiment, or
- balanced net sentiment

Two Approaches to Sentiment

- The supervised ML approach
- The unsupervised lexical KB approach



vs.

Recommended ML Approach in Python

- Can use `sklearn` to import the SDG classifier (an SVM implementation)*
- Use to make a binary classifier from training data of both negative and positive sentiment

**As in Sarkar (2016) pp. 349 ff*

ML Approach: Pros and Cons

Pros

- Quick to implement when a large amount of training data is ready-to-hand (many thousands of example texts)
- Don’t need to develop a coded vocabulary

ML Approach: Pros and Cons

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- Quick to implement when training data is ready-to-hand
- Don’t need to develop a coded vocabulary

Cons

- Very opaque (not XAI)
- Only as granular as the training data annotations (usually not very)

Sentiment Analysis with ML

Outline of Procedure

1. Establish a training set.

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2. Normalize texts.

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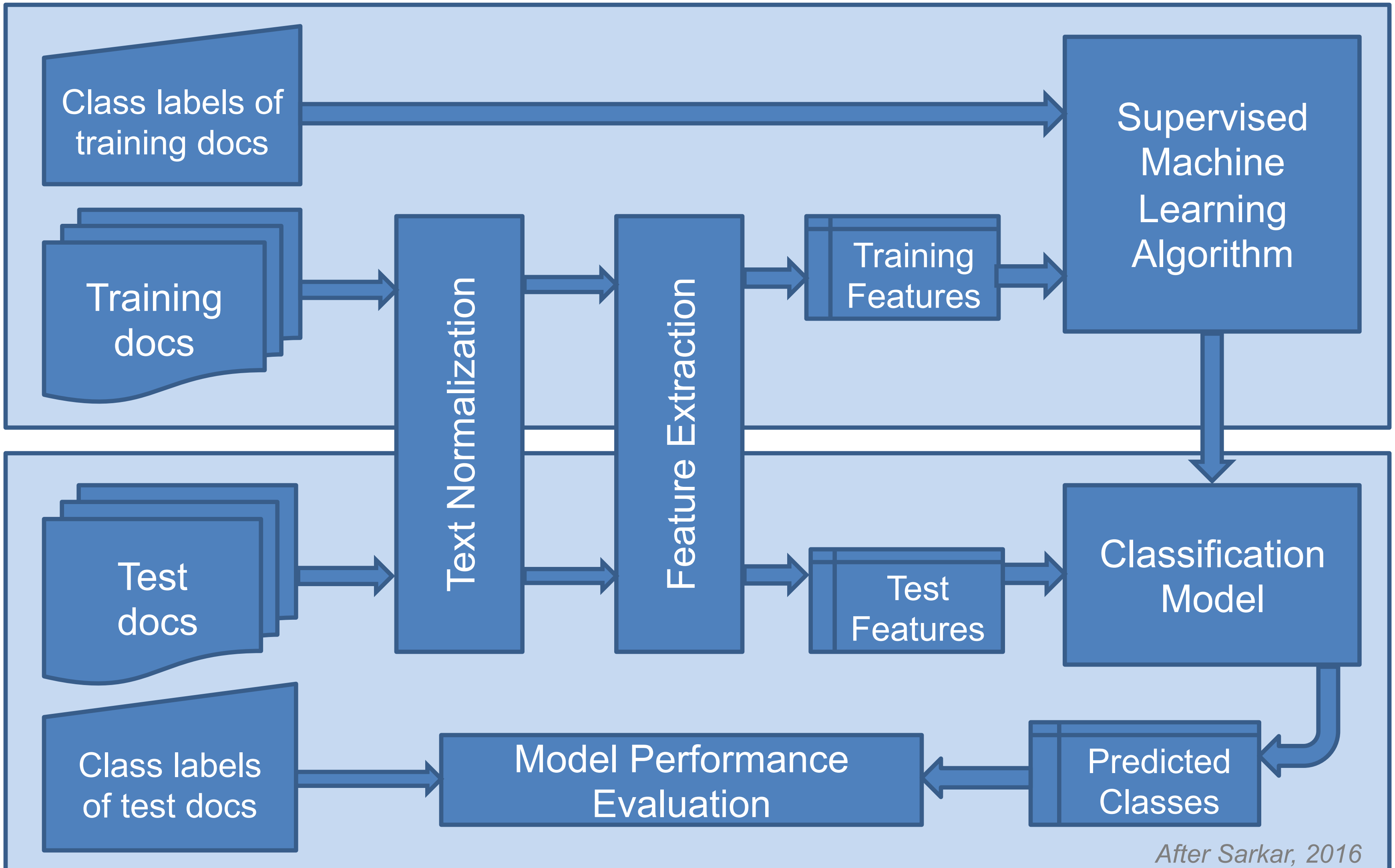
5. After QA, decide if more training data is needed.

Sentiment Analysis Blueprint: ML Approach



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Semantic Analysis: Lexical-Based Sentiment Analysis

Natural Language Processing

Lexical Approach in Python

The biggest decision is choosing a sentiment vocabulary:

- AFINN (“**A**ffective lexicon by **Finn** Nielsen”): 2,477 clues

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Lexical Approach in Python

The biggest decision is choosing a sentiment vocabulary. Options are:

- AFIN
- Liu's
- MPQ … y
  lexic
- Senti
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- VADE … g):
  7,500
- Patte
  IDs from WordNet, valences hand coded or inferred from a nearest neighbor)
- Custom lexicon: as many clues as you dare!

Does size matter?
Larger size is always nice, but some smaller sentiment libraries, if well constructed, can outperform larger ones.

Lexical KB Approach: Pros & Cons

Pros

- Does not require training data to get started (though it’s recommended to have some)
- Eminently explainable (good XAI)

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- Does not require training data to get started (though it's recommended to have some)
- Eminently explainable (good XAI)

Cons

- Needs a coded vocabulary (lexical KB)
- Can be cumbersome to maintain in the face of new tropes

Sentiment Analysis with Lexical KB

Outline of Procedure

1. Establish valence-weighted vocabularies.

Sentiment Analysis with Lexical KB

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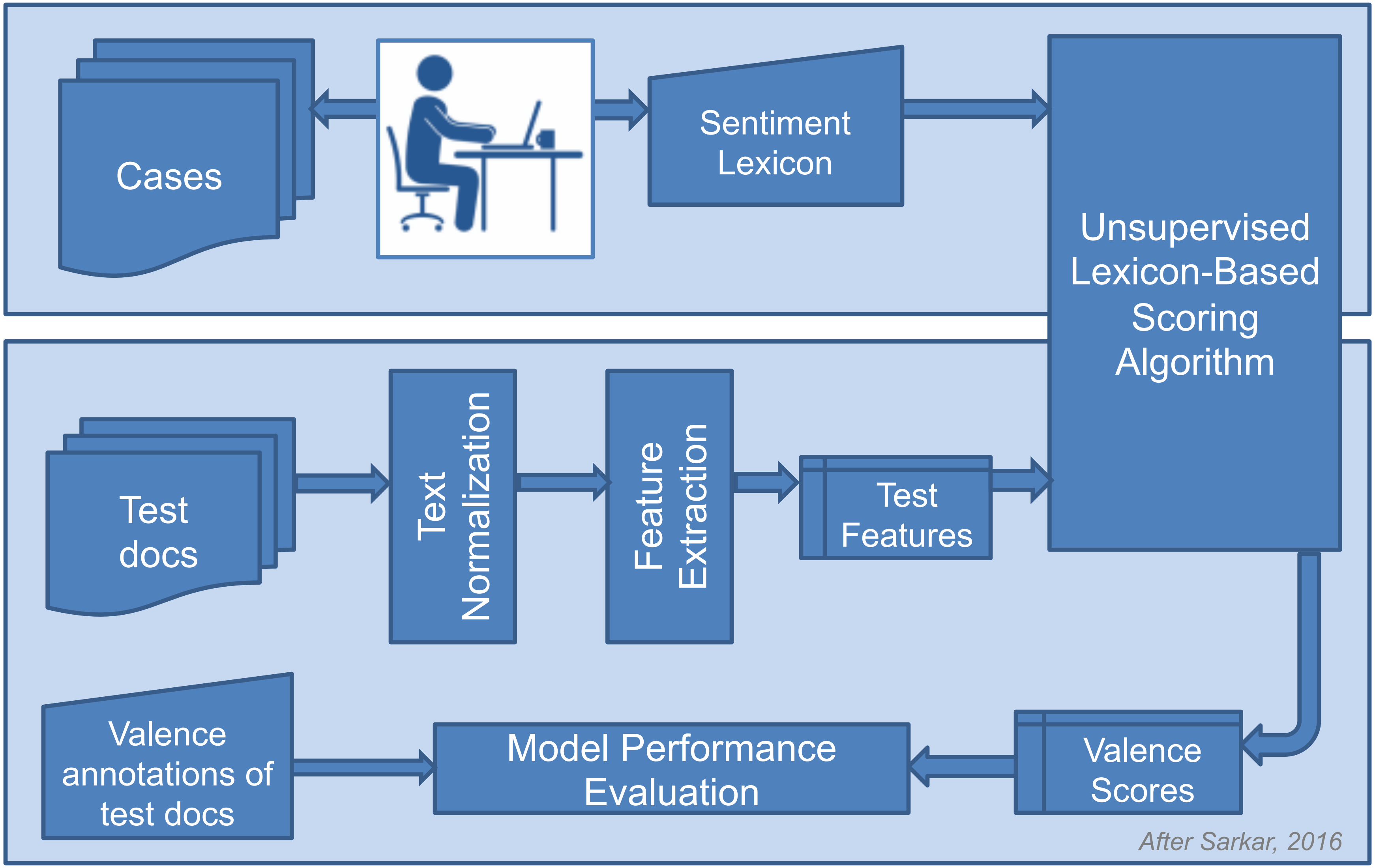
Sentiment Analysis with Lexical KB

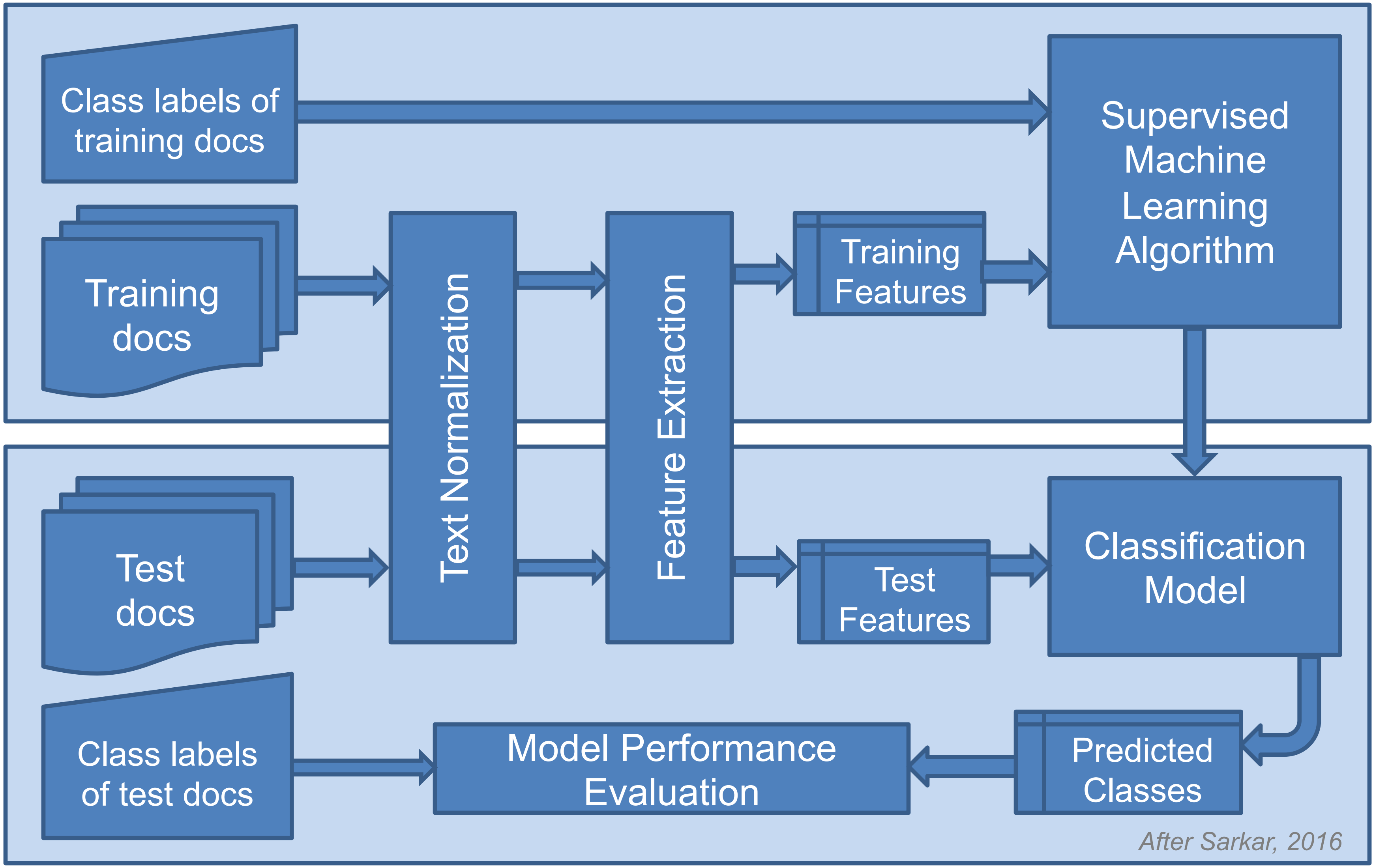
Outline of Procedure

1. Establish valence-weighted vocabularies.
2. Normalize texts.
3. Extract feature vectors.
4. Execute a scoring algorithm.
5. After QA, tweak vocabulary and rerun until it passes QA.

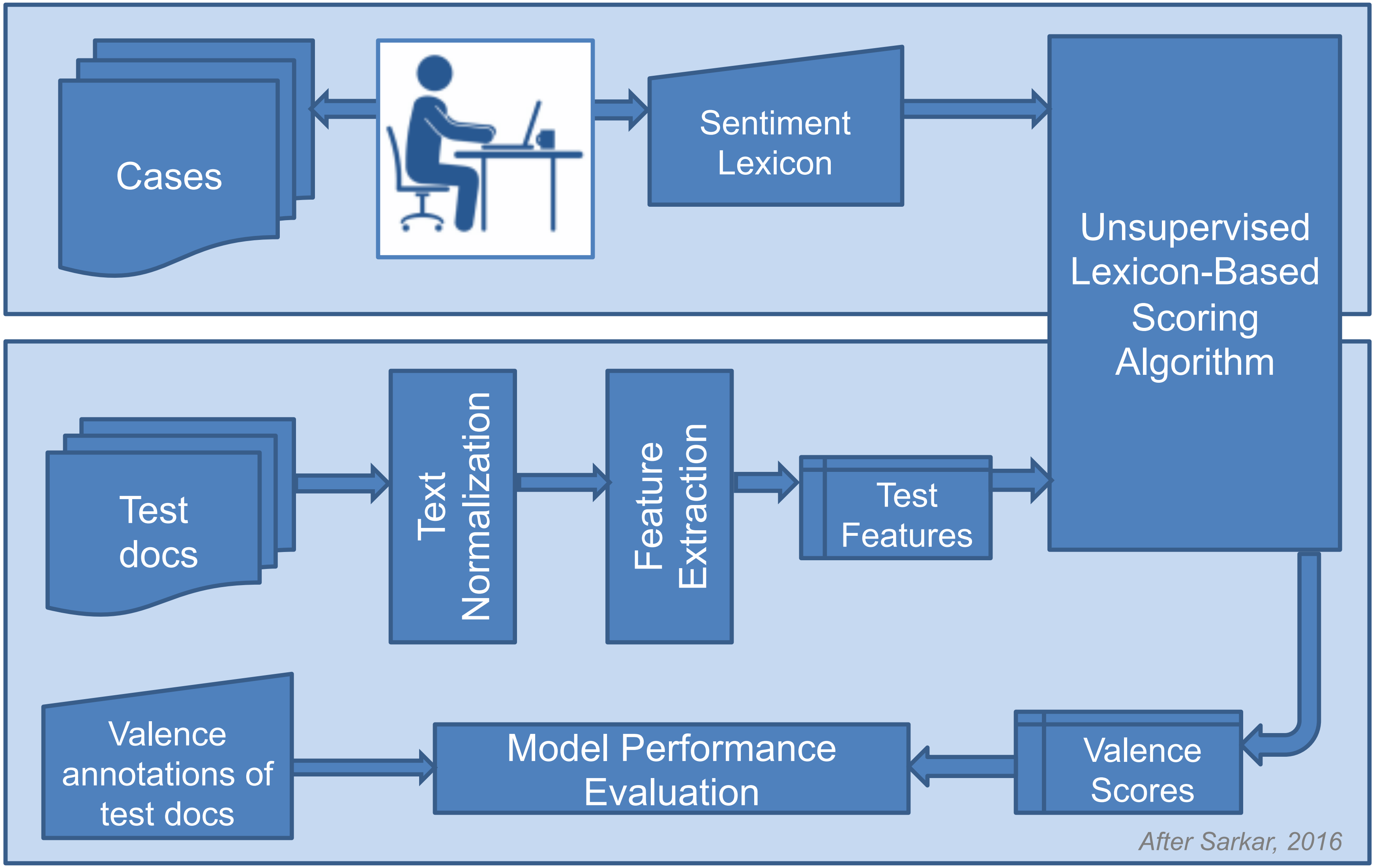
Sentiment Analysis Blueprint: Lexical KB Approach



Recalling Our Sentiment Analysis Blueprint: ML Approach



Sentiment Analysis Blueprint: Lexical KB Approach



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Semantic Analysis:
Advanced Sentiment Analysis

Natural Language Processing

Beyond General Sentiment Scoring

We will cover three ways to improve on general sentiment scoring:

- Determining referents and/or topics to which sentiment attaches
- Classifying sentiment into more categories than just negative and positive
- Picking up on non-sentiment vocabulary differences that align with sentiment around a topic, e.g., how rhetoric aligns with sentiment on an issue

Sentiment Reference

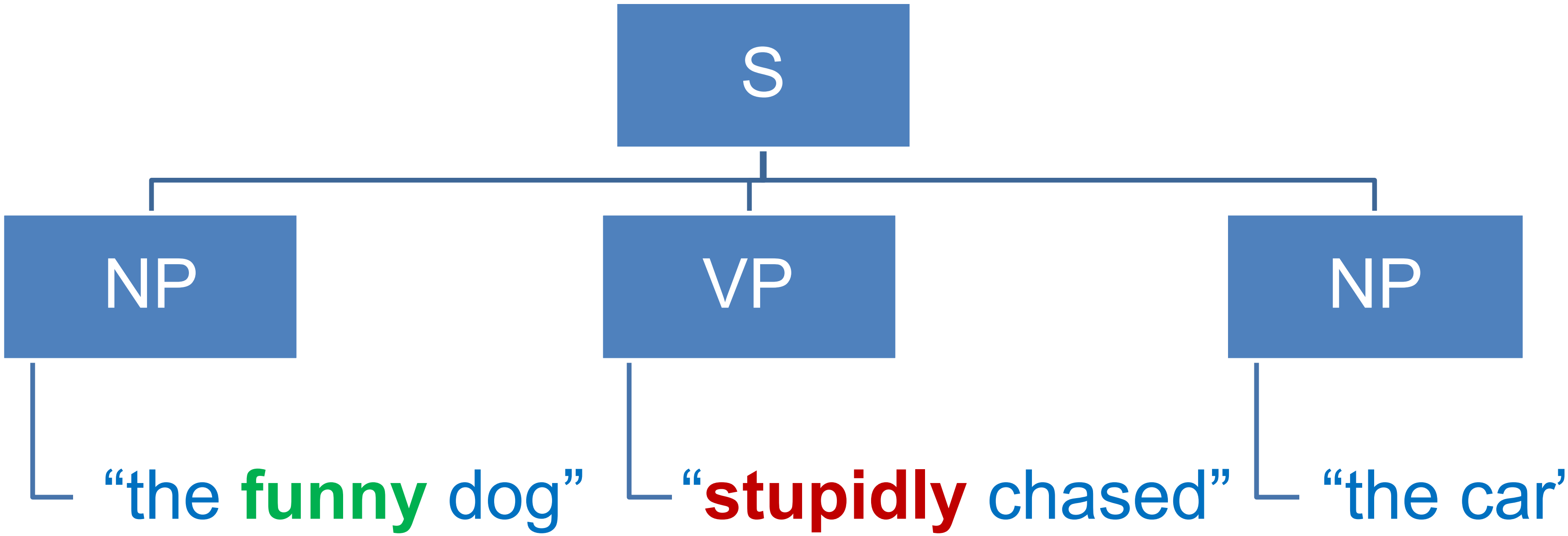
Attaching sentiment to objects or topics is so challenging that few organizations attempt it today in a commercial setting.

- Nonetheless, it’s worthwhile.

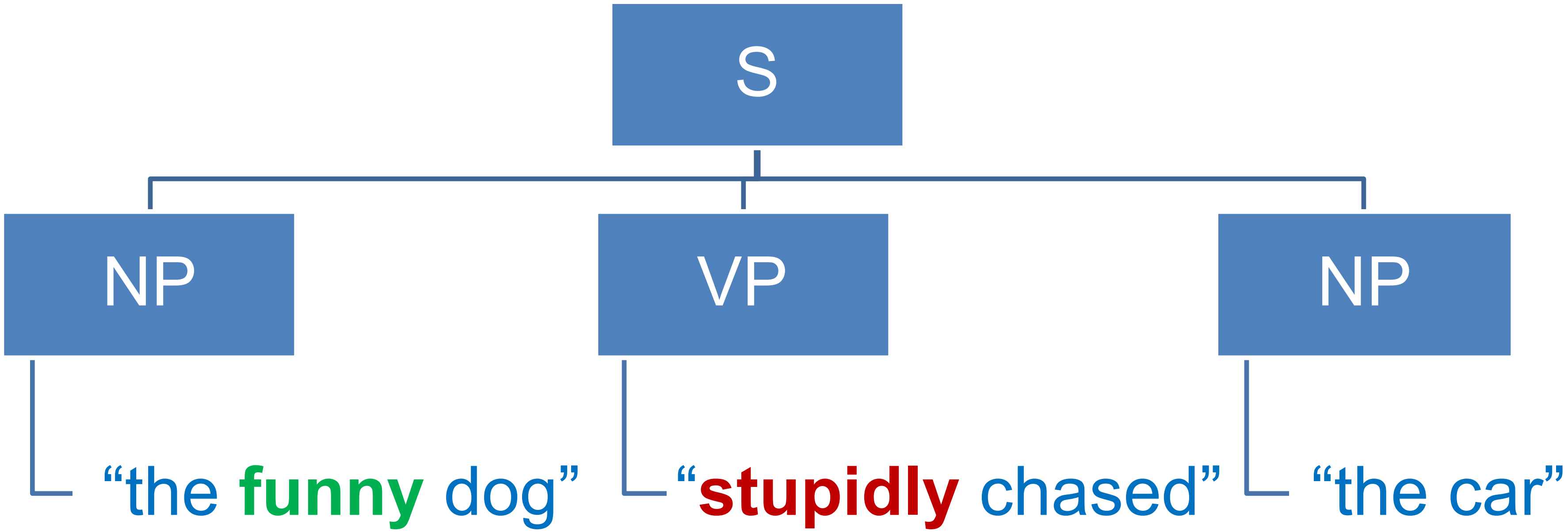
Sentiment Reference

- A straightforward approach is just to run a chunker, and send NP-chunks and VP-chunks, instead of sentences, into the sentiment analyzer.
- You then presume the main noun (or verb) in a chunk is the object of any sentiment expressed in its chunk, which will *usually* be true.
    - There are arguable cases: in "the hideously clad delivery boy," does the negative sentiment of "hideously" apply to the "boy"?

Using Chunks with Sentiment Analysis



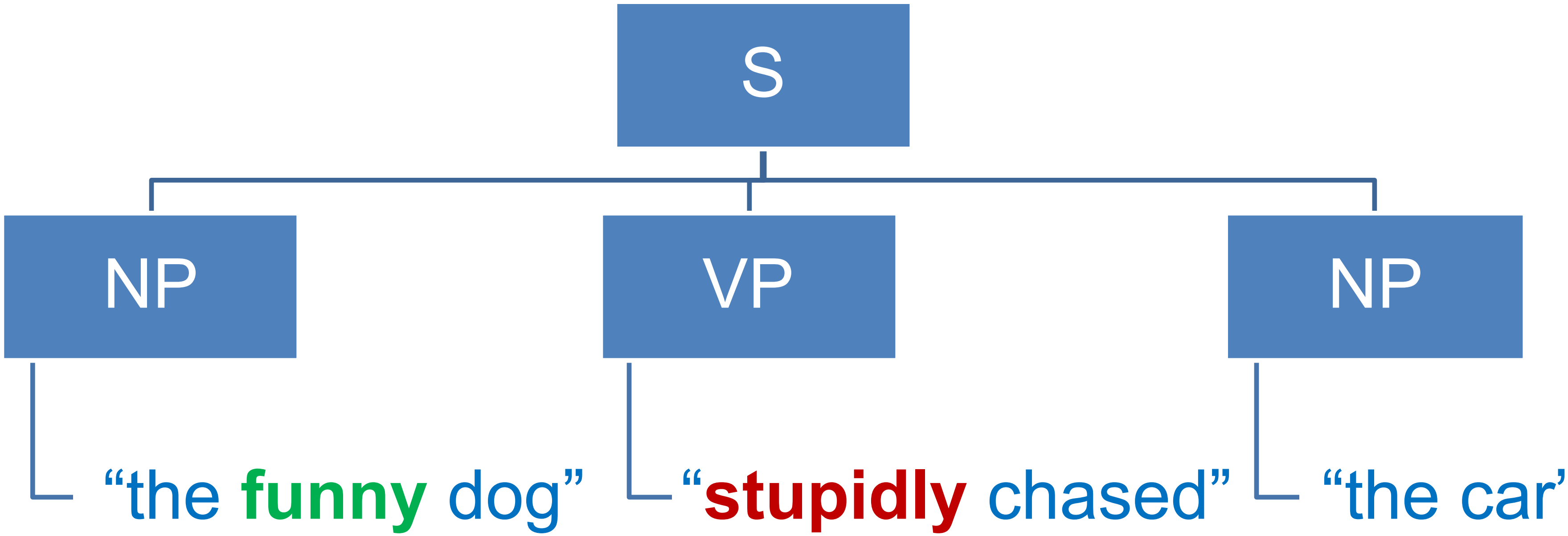
Using Chunks with Sentiment Analysis



We can stem any verb to its *lemma* and then take the gerund form.
That lets us output:

chasing: negative
dog: positive

Using Chunks with Sentiment Analysis



We can stem any verb to its *lemma* and then take the gerund form.
That lets us output, with weights:

chasing: -0.3
dog: +0.5

Sentiment Reference

There are some vulnerabilities of this approach.

The first is negation: consider “the not unappealing actress.”

Negation: Ignore or not?

When doing general sentiment detection (merely negative or positive) over multi-sentence text units, we can often just neglect negation since it “cancels out” over multiple instances of sentiment.

- But we’ll see that when we are refining our treatment of sentiment with higher dimensionality, it becomes awkward to turn out false readings because of negation.

Sentiment Reference

Another vulnerability:

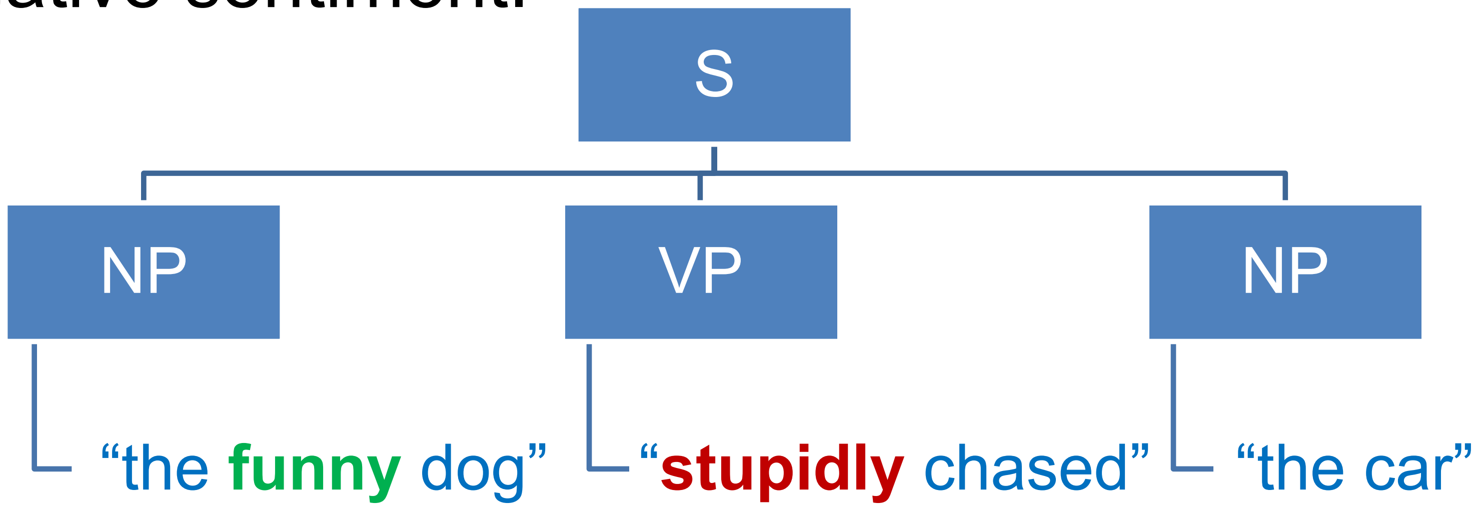
Some sentiment will attach outside the NP-chunk instead of within it:

“The young actor’s performance was disappointing.”

(What is the NP-chunk here? Notice it doesn’t contain the sentiment!)

Using Chunks with Sentiment Analysis

Notwithstanding the various warnings or pitfalls, this approach, when coupled with a large-enough sample size, will give us directionally correct results, e.g., will point out the nouns frequently attached to more positive vs. negative sentiment.

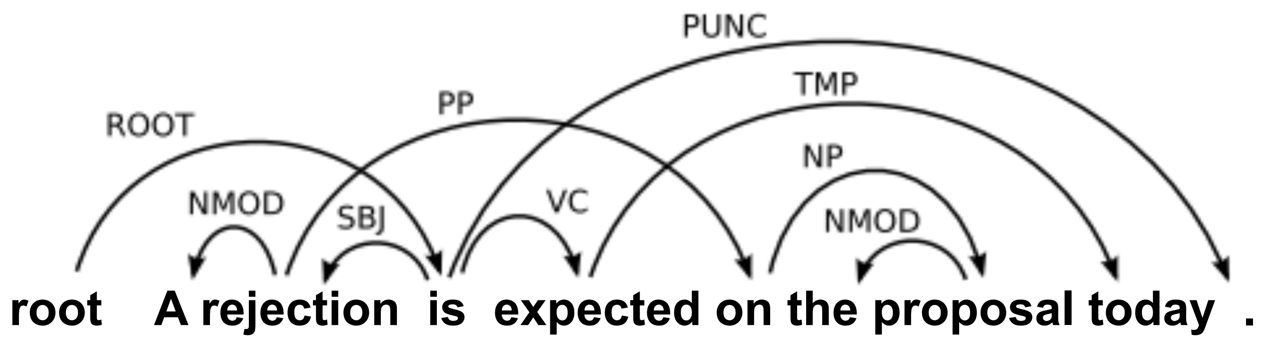


More Advanced Approaches

- Run a dependency parser.
- Follow dependency paths from a sentiment trigger until an object (e.g., an NP) is found.

Sentiment Dependency Tracing

Tracing from “rejection,” follow arrows until you get to an NP.



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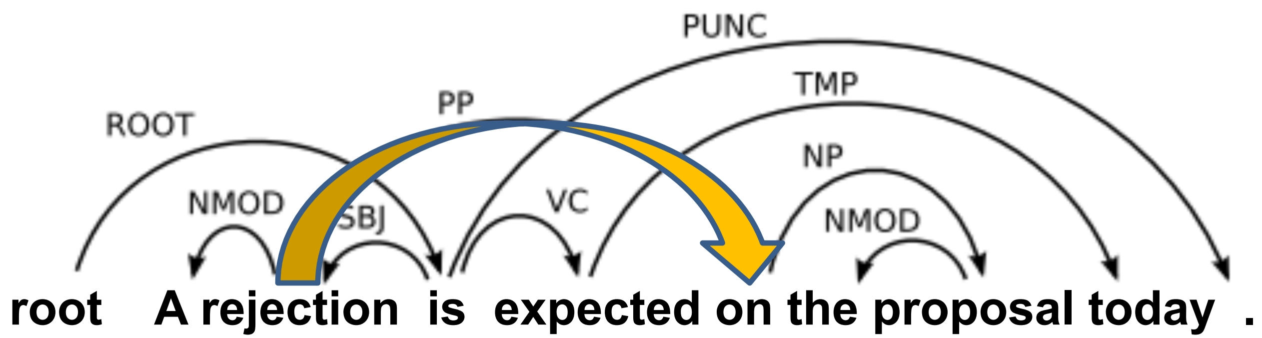

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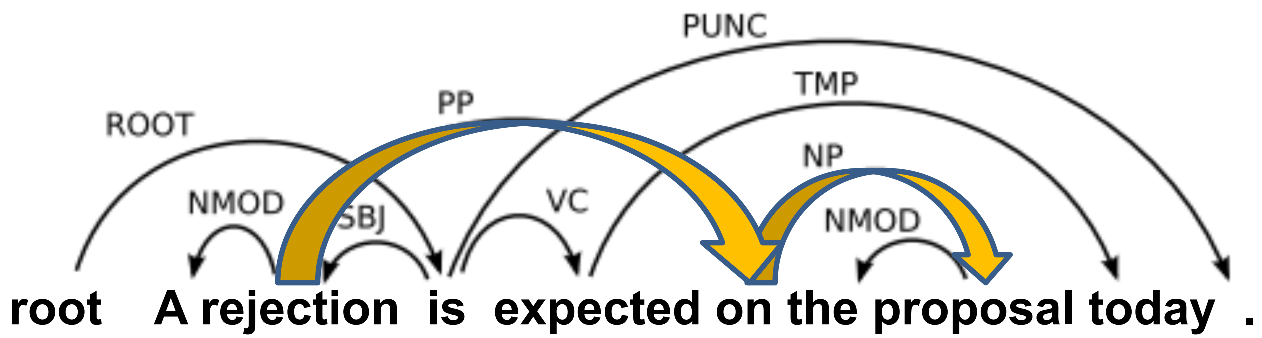

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Semantic Analysis: Hierarchical Sentiment Scoring

Natural Language Processing

Dimensionality of Sentiment

By default we have one dimension (polarity) or two (negative-positive), but in real life there are many more dimensions:

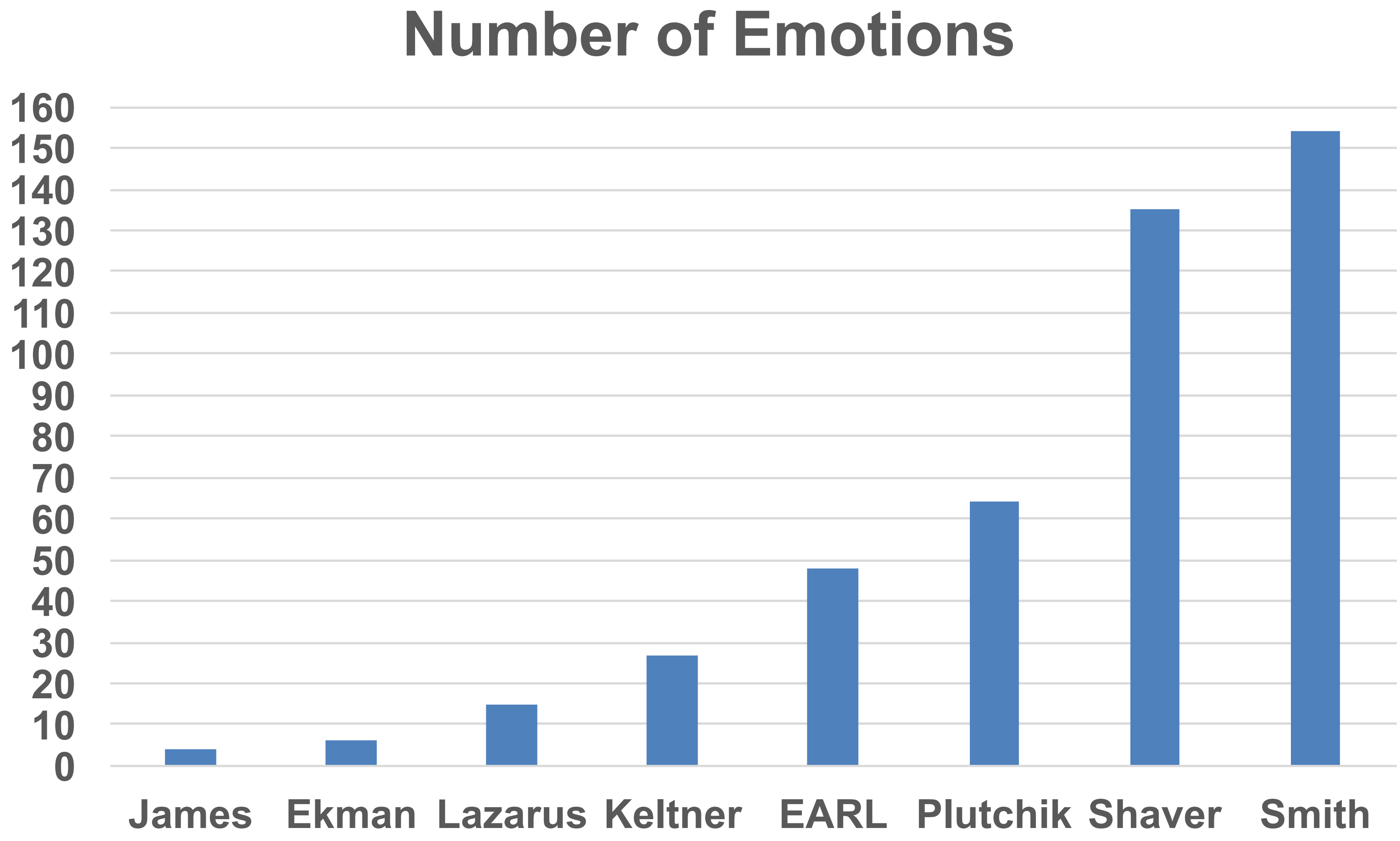
- Negative sentiment breaks down into: sad, angry, worried, grieving, etc.
- Positive sentiment breaks down into: serene, joyful, confident, relieved, etc.

Typologies of Emotion

Creator(s)	Number of Emotions
• James (1890):	**4**
• Ekman (1992):	**6**
• Lazarus (1996):	**15**
• Keltner (2017):	**27**
• EARL (2006):	**48**
• Plutchick-Hagy (1980, 2012):	**64**
• Shaver-Parrot (1987, 2001):	**135**
• Watt Smith (2015):	**154**

Notice an interesting trend in the numeration?

Typologies of Emotion



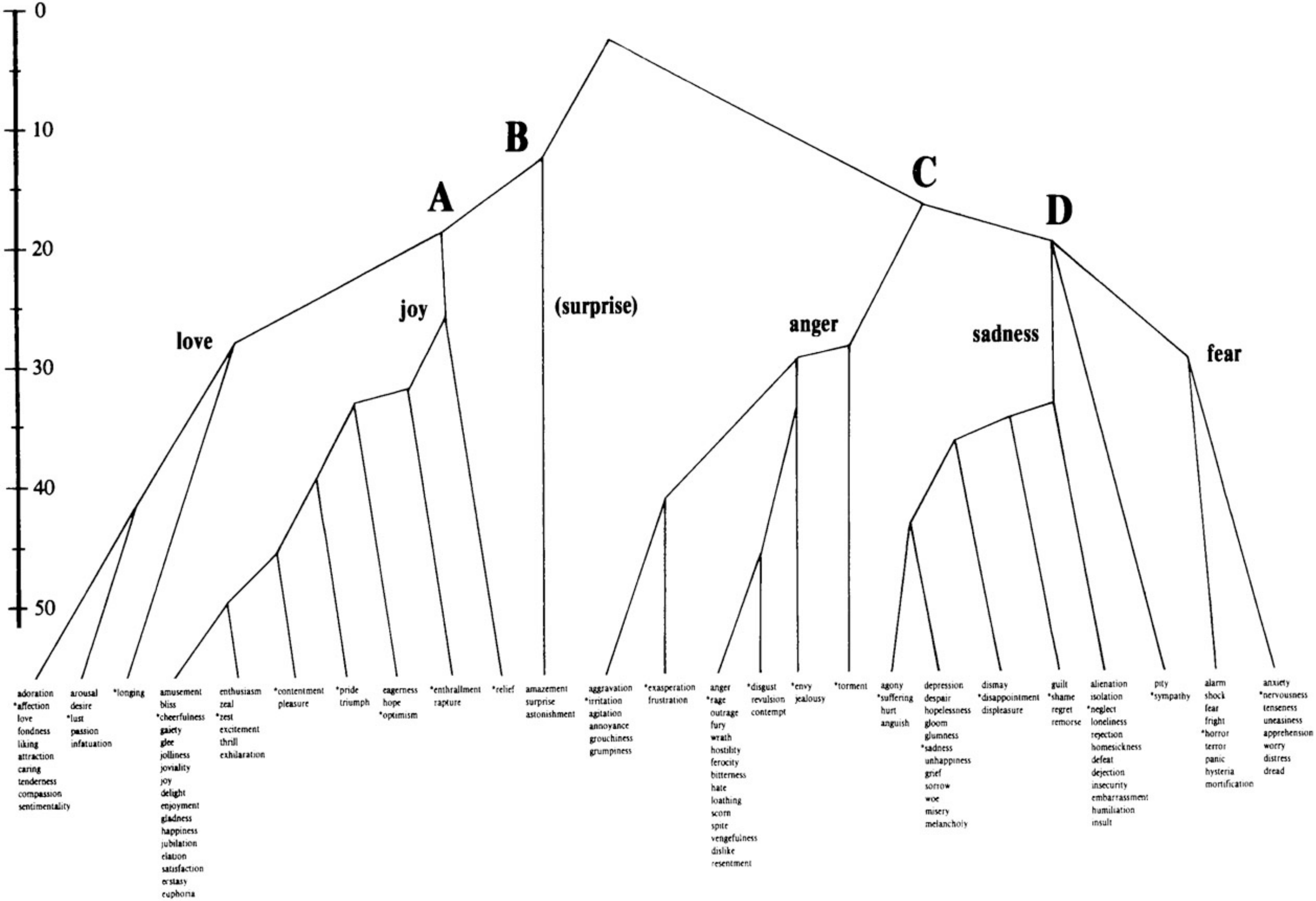
Typologies of Emotion

For something manageable, we can use the Shaver (1987) set of these six:

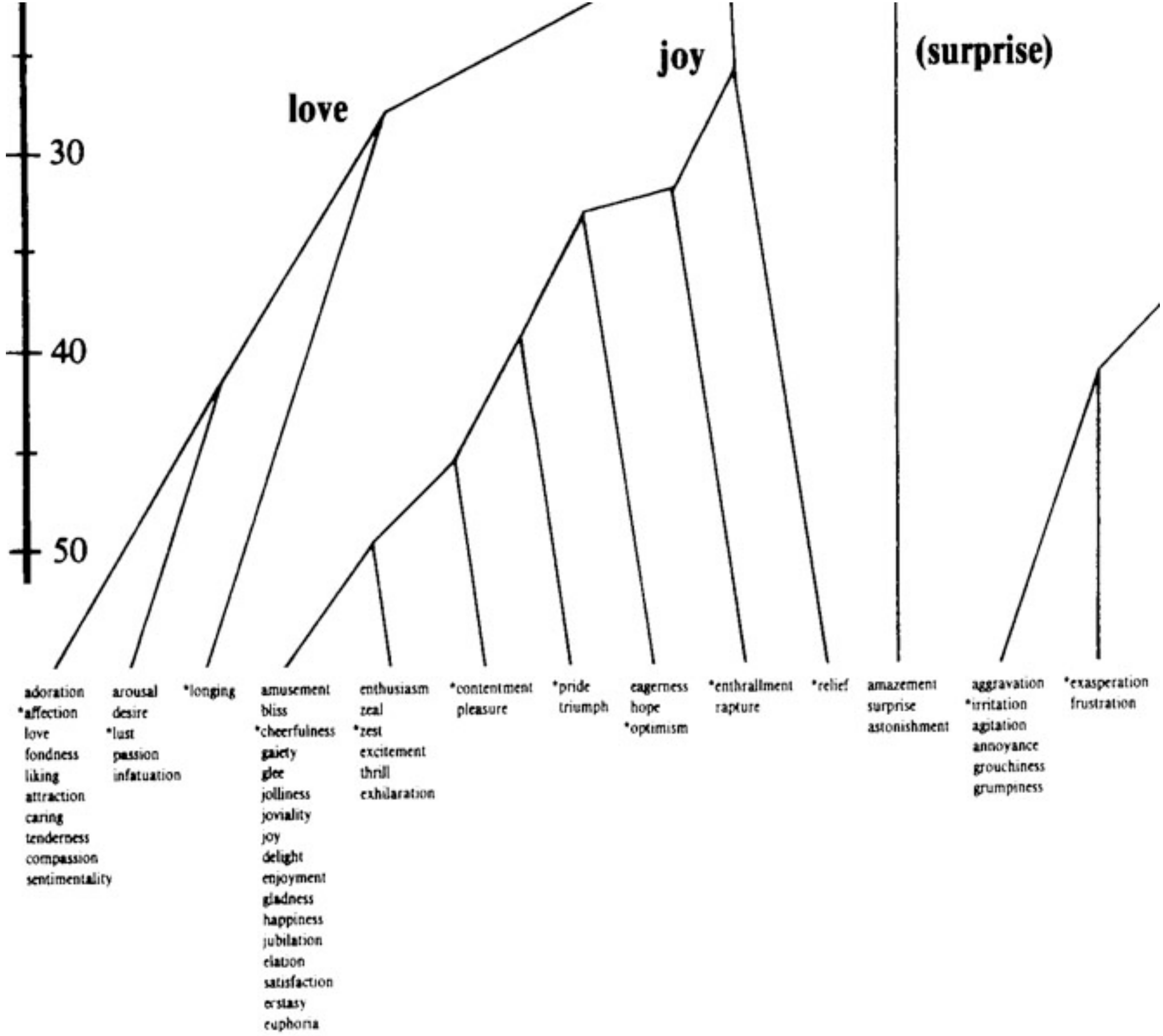
- Positive emotions: love, joy, surprise
- Negative emotions: anger, sadness, fear

Shaver’s Hierarchy of Emotions

- Has the benefit of setting us up for developing more granularity, as these 6 first-level emotions are broken down into second-level and third-level emotions, hierarchically, for a total of 135 distinct emotions.
- So for now let’s just deal with Shaver’s first level, keeping in mind there is above it a “zeroth” level of simply negative-positive.



0
10
20
30
40
50
A
B
C
D
love
joy
(surprise)
anger
sadness
fear
adoration *affection love fondness liking attraction caring tenderness compassion sentimentality
arousal desire *lust passion infatuation
*longing
amusement bliss *cheerfulness gaiety glee jolliness joviality joy delight enjoyment gladness happiness jubilation elation satisfaction ecstasy euphoria
enthusiasm zeal *zest excitement thrill exhilaration
*contentment pleasure
*pride triumph
eagerness hope *optimism
*enthrallment rapture
*relief
amazement surprise astonishment
aggravation *irritation agitation annoyance grouchiness grumpiness
*exasperation frustration
anger *rage outrage fury wrath hostility ferocity bitterness hate loathing scorn spite vengefulness dislike resentment
*disgust revulsion contempt
*envy jealousy
*torment
agony *suffering hurt anguish
depression despair hopelessness gloom glumness *sadness unhappiness grief sorrow woe misery melancholy
dismay *disappointment displeasure
guilt *shame regret remorse
alienation isolation *neglect loneliness rejection homesickness defeat dejection insecurity embarrassment humiliation insult
pity *sympathy
alarm shock fear fright *horror terror panic hysteria mortification
anxiety *nervousness tenseness uneasiness apprehension worry distress dread



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40
50
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(surprise)
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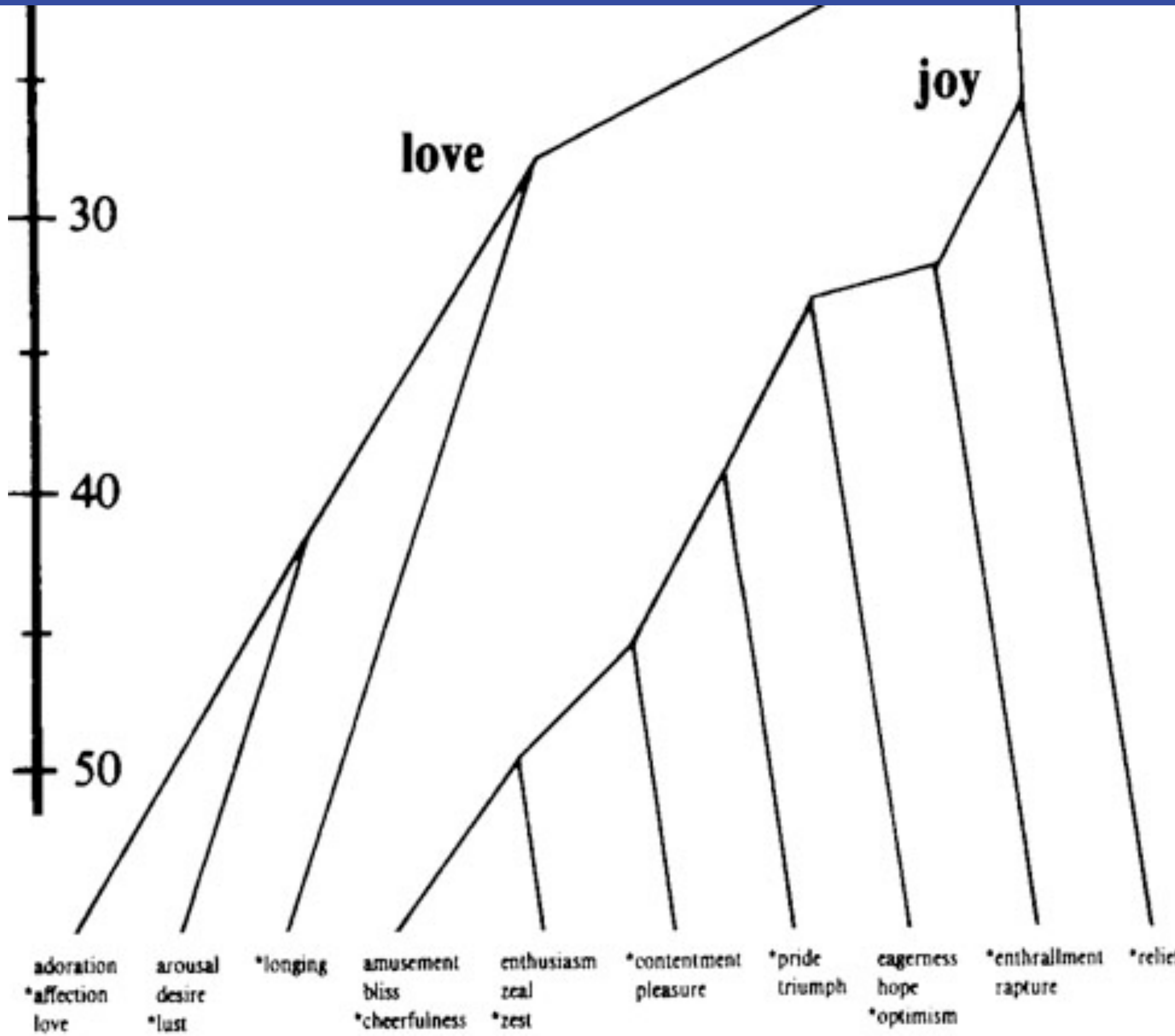
love
fondness
liking
attraction
caring
tenderness
compassion
sentimentality
arousal
desire
*lust
passion
infatuation
*longing
amusement
bliss
*cheerfulness
gaiety
glee
jolliness
joviality
joy
delight
enjoyment
gladness
happiness
jubilation
elation
satisfaction
ecstasy
euphoria
enthusiasm
zeal
*zest
excitement
thrill
exhilaration
*contentment
pleasure
*pride
triumph
eagerness
hope
*optimism
*enthrallment
rapture
*relief
amazement
surprise
astonishment
aggravation
*irritation
agitation
annoyance
grouchiness
grumpiness
*exasperation
frustration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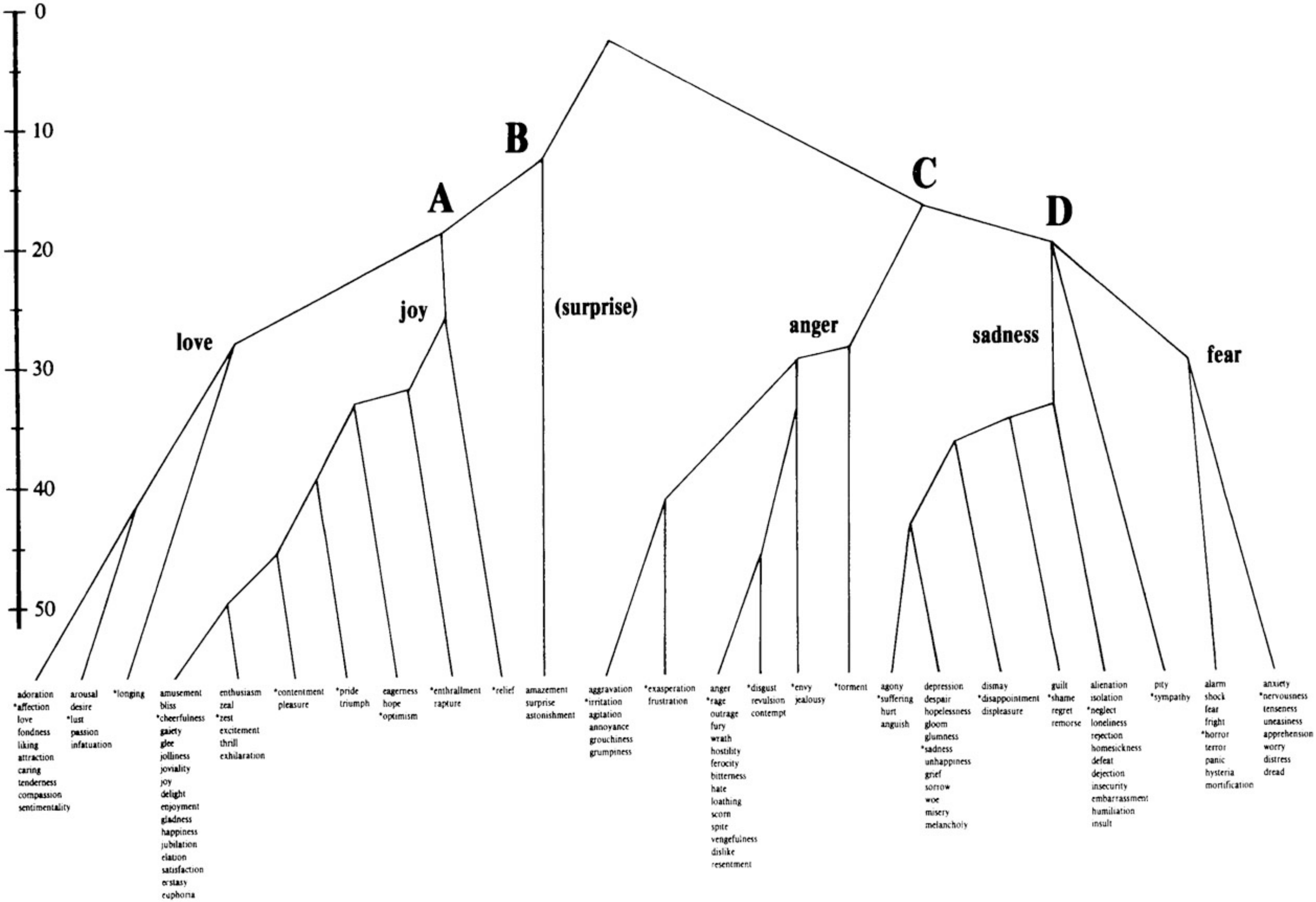

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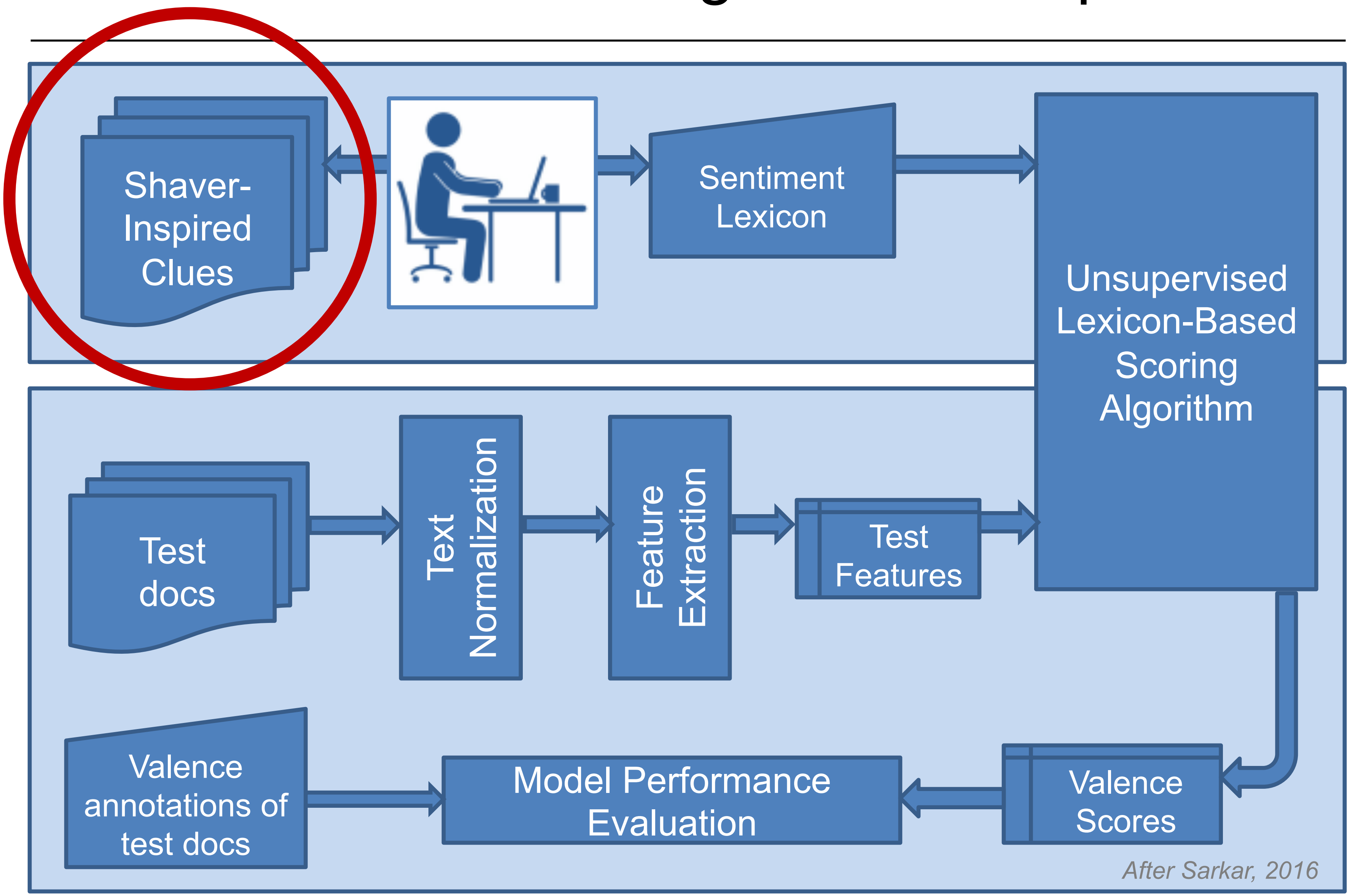
pity *sympathy
alarm shock fear fright *horror terror panic hysteria mortification
anxiety *nervousness tenseness uneasiness apprehension worry distress dread

Leveraging the Hierarchy

- The nice thing is we can use all the labels of deeper levels as clues (trigger words) to identify the first level—so we have a ready-made starter vocabulary.

How Shaver Changes Our Blueprint



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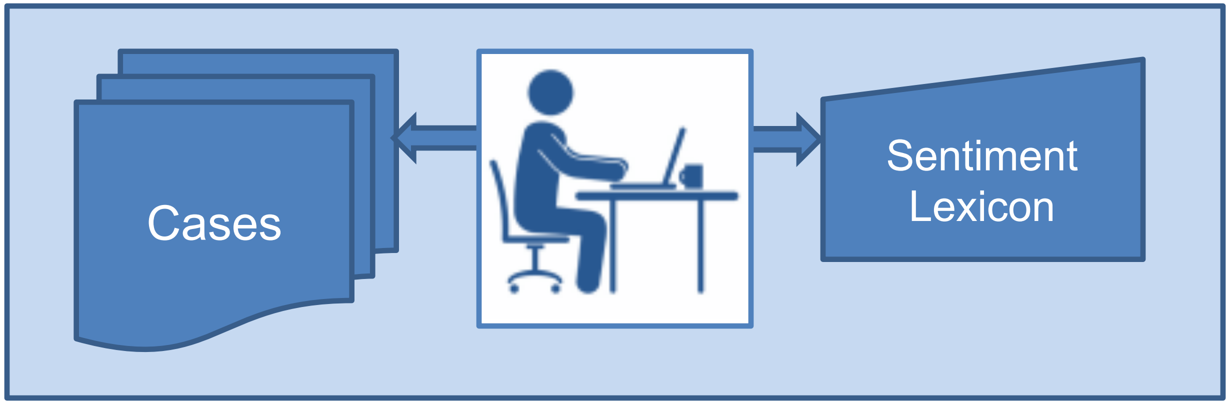
Semantic Analysis:
A Hybrid Approach—Semiautomated Feature Engineering for Sentiment Lexicography

Natural Language Processing

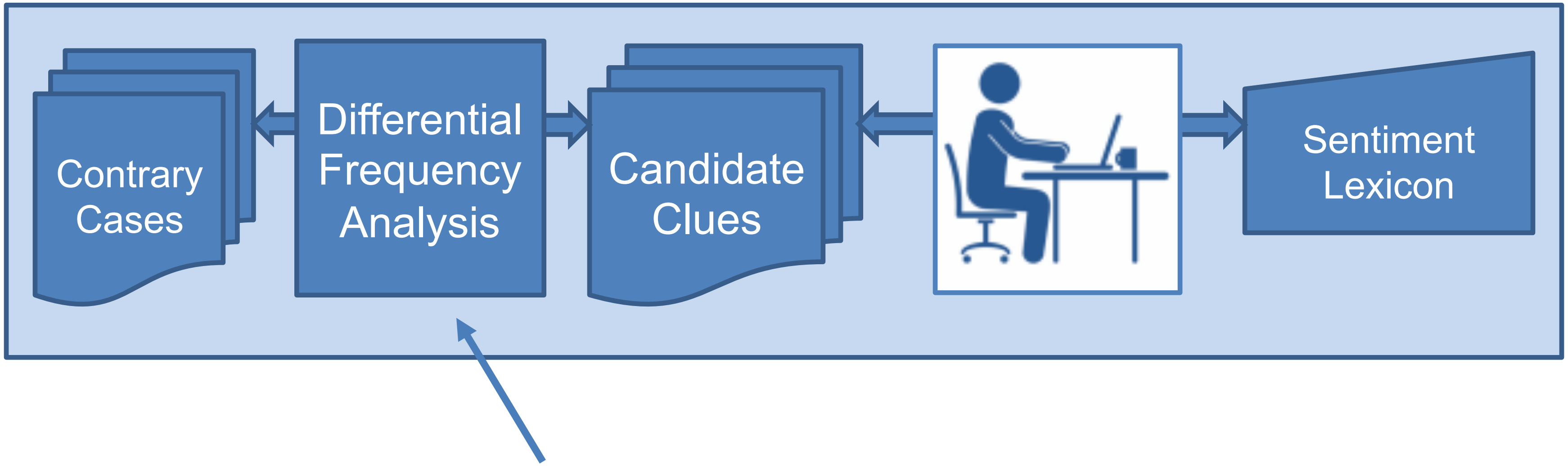
A Hybrid Approach

We can help this person out.



A Hybrid Approach

Here's how we do it.



This part is akin to some of our familiar IE and ML methods.

Example: Handling User Reviews

We usually have an ordinal rating scale, e.g., 1 to 5 stars.

Customer Reviews

153

3.7 out of 5 stars

5 star	53%
4 star	15%
3 star	12%
2 star	8%
1 star	12%

SONY Over Ear Best Stereo Extra Bass Portable H...

by Sony

Price: $17.38 prime

Write a review

Top positive review

See all 104 positive reviews ›

6 people found this helpful

Sony is Sony

By Suchit Patil on December 28, 2016

Quality product from SONY again. Good quality head phones.Use it wile travelling, workouts , fitness regimes, camping. take it where ever you go.

Top critical review

See all 49 critical reviews ›

2 people found this helpful

Totally worthless, throwaway item. DOA.

By Amazon Customer on May 15, 2018

The left earphone does not work at all, meaning the unit is worthless. I read the warranty and it requires repacking in the original materials and then paying postage to send to get a "refurbished" replacement. The first problem is that there is no way to get the unit out of the original packaging without damaging the packing material. I was just looking for an inexpensive set to use for travel, easy packing in briefcase what I got was useless, sorry to say. Have never had this issue with SONY before, but this item is a throw away.

User Reviews as Training Data

- Three-star reviews are troublesome because they can either be neutral or mildly bad or mildly good.
- So it’s generally the safest bet to separate 4s and 5s from 1s and 2s, ignoring 3s (because of their ambiguity), to use as training data.

A Mixed Approach

- We can use a semiautomated feature engineering.
  - Borrow some of the power of ML techniques.
  - Bootstrap the lexical approach to developing clues.
- Very straightforward to implement with 5-star user reviews.
  - Generally 1- and 2-star reviews are negative, while 4- and 5-star reviews are positive.
- We can dovetail the adding of dimensions to the manual coding process of the feature engineering output.

A Mixed Approach

Further benefits of the mixed approach

- Knowledge engineers can select dimensions or themes when they approve candidate clues that were outputted by the automated phase.
  - You can even force the selection of a dimension or theme as the way to approve a candidate clue.
- We maintain XAI at lower cost (smaller time investment) than if we did 100% manual feature engineering.

Here's What It Can Look Like

This is what the lexicographer initially sees.

These are all candidate clues derived from a differential frequency analysis of contrastive reviews of laptops.

Notice the Theme column is blank.

Phrase	Theme	Valence Score
above average		0.3
absolutely amazing		0.82
absolutely clear		0.11
absolutely love		0.87
absolutely loving		0.21
accented beautifully		0.23
access speed		0.04
actually heavier		-0.38
actually lighter		0.42
actually outweigh		-0.38
actually weighs		0.04
actually works		0.45
added features		0.08
added weight		-0.17
adds weight		-0.17
adequate speed		0.23
adequate storage		0.23
affordable laptop		0.47
affordable price		0.5
affordable reliable		0.42
affording ease		0.42
after days		0.81
almost instant		0.45

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actually weighs		0.04

Here’s What It Can Look Like

Now the lexicographer has started labeling the candidate clues.

Notice she leaves some of them blank; they will not be used.

By assigning different themes, we customize our sentiment lexicon for analyzing opinions on laptops.

Phrase	Theme	Valence Score
above average	Praise	0.3
absolutely amazing	Praise	0.82
absolutely clear		0.11
absolutely love	Praise	0.87
absolutely loving	Praise	0.21
accented beautifully	Design	0.23
access speed		0.04
actually heavier	Weight	-0.38
actually lighter	Weight	0.42
actually outweigh	Weight	-0.38
actually weighs		0.04
actually works	Reliability	0.45
added features	Features	0.08
added weight		-0.17
adds weight	Weight	-0.17
adequate speed	Performance	0.23
adequate storage	Storage	0.23
affordable laptop	Value	0.47
affordable price	Value	0.5
affordable reliable	Reliability	0.42
affording ease	Ease of Use	0.42
after days		0.81
almost instant	Performance	0.45

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actually outweigh	Weight	-0.38
actually weighs		0.04

Here’s What It Can Look Like

After a lot of work selecting themes, we can sort the list by theme.

Here are a bunch of negative sentiment clues with Theme = Battery.

Phrase	Theme	Valence Score
battery stopped	Battery	-0.81
battery fiasco	Battery	-0.79
defective battery	Battery	-0.79
horrible battery	Battery	-0.79
battery out	Battery	-0.62
battery died	Battery	-0.62
dying battery	Battery	-0.62
battery dies	Battery	-0.61
bad battery	Battery	-0.61
battery issue	Battery	-0.58
limited battery	Battery	-0.58
puny battery	Battery	-0.58
battery issues	Battery	-0.58
poor battery	Battery	-0.57
battery only	Battery	-0.44
battery problems	Battery	-0.41
dead battery	Battery	-0.41
battery depleted	Battery	-0.38
battery drain	Battery	-0.38
eat battery	Battery	-0.38
less battery	Battery	-0.38
non-removable battery	Battery	-0.38
overstating battery	Battery	-0.38

Here's What It Can Look Like

Phrase	Theme	Valence Score
battery stopped	Battery	-0.81
battery fiasco	Battery	-0.79
defective battery	Battery	-0.79
horrible battery	Battery	-0.79
battery out	Battery	-0.62
battery died	Battery	-0.62
dying battery	Battery	-0.62
battery dies	Battery	-0.61
bad battery	Battery	-0.61
battery issue	Battery	-0.58
limited battery	Battery	-0.58

Here's What It Can Look Like

And here are a bunch of positive sentiment clues with Theme = Ease of Use.

Voila! We have an excellent multithemed sentiment lexicon for evaluating laptop reviews!

Phrase	Theme	Valence Score
very comfortable	Ease of Use	0.69
very easy	Ease of Use	0.68
really easy	Ease of Use	0.68
very convenient	Ease of Use	0.68
amazing ease	Ease of Use	0.62
surprising ease	Ease of Use	0.62
great ease	Ease of Use	0.62
overall ease	Ease of Use	0.62
convenience of	Ease of Use	0.5
easier than	Ease of Use	0.5
very easily	Ease of Use	0.5
very handy	Ease of Use	0.48
easily portable	Ease of Use	0.47
easy access	Ease of Use	0.47
easy set	Ease of Use	0.47
more convenient	Ease of Use	0.47
extremely portable	Ease of Use	0.45
relative ease	Ease of Use	0.43
affording ease	Ease of Use	0.42
ease-of-use make	Ease of Use	0.42
immediately eased	Ease of Use	0.42
of ease	Ease of Use	0.39
easy enough	Ease of Use	0.32

Here's What It Can Look Like

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overall ease	Ease of Use	0.62
convenience of	Ease of Use	0.5
easier than	Ease of Use	0.5
very easily	Ease of Use	0.5
very handy	Ease of Use	0.48

Let’s Look a Little Closer

What’s going in here?

Phrase	Theme	Valence Score
worked fine	Reliability	-0.43
working fine	Reliability	0.14

Let’s Look a Little Closer

What’s going in here?

Phrase	Theme	Valence Score
worked fine	Reliability	-0.43
working fine	Reliability	0.14

The autogenerated valences tell the story.
When would you write “worked [past tense] fine” in a review of a laptop?

Let’s Look a Little Closer

What’s going in here?

Phrase	Theme	Valence Score
worked fine	Reliability	-0.43
working fine	Reliability	0.14

This is why we don’t stem the words in these clues. Stemming is not always a good idea!

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Semantic Analysis:
Sentiment and Insight

Natural Language Processing

Presentation of Sentiment

In a commercial setting, sentiment analysis is not an end in itself. Your stakeholders want you to deliver *actionable insights.*

How can you do that?

Leveraging Sentiment for Insights

Roll-ups with examples are usually helpful.

- For product reviews: roll-up aggregate results by theme, and show examples.
- For politics: make a candidate-issue matrix with net sentiment balance, and link to examples.

Example: Product Review Roll-Up

Dell Inspiron i5559-4682SLV 15.6 Inch FHD Touchscreen Signature Edition Laptop with Intel RealSense

Reviews Analyzed: 39

Date Range: 5/5/2016 to 1/29/2017

Average Rating: 3.9

Battery★★★★★

4.0 | | I've had this computer for 3 months already and i'm quite satisfied. the only negative comments are that 1. I've had an issue playing a DVD from it with power DVD. It has frozen on me a couple of times to the point where i had to shut it off and lose some of my work. Otherwise it's a great computer. It's fast. *It has a battery life ranging from 1-1/2 hrs*. to 4-1/2 hrs depending how heavily your using it and fully charges about 1% a minute. It is a bit heavy . I walk 20 minutes every day with it and it's not so much fun. The touch screen is nice as is windows 10. it's got plenty of ram and storage space, 3 USB Drives, CD/DVD/RW Drive and and is overall quite a powerful computer considering the price i paid for it.

5.0 | | This is really a fantastic computer. You will be hard-pressed to find any other computer for the price that does what this thing can do. 6th Generation Intel i5 (the latest CPU), 8 GB of memory, 1 TB hard drive, 15" touchscreen, 1920x1080 resolution, and comes with Windows 10. *I do think the battery life could be improved, but most computers on the market have that challenge.* Haven't had any issues thus far with the laptop and I'm extremely happy with the price that was paid for it.

Display★★★★★

5.0 | | *The laptop has a beautiful display, and was pretty responsive.* There was no crapware installed with the system, which is a nice touch. The only problem I had with this laptop is that it lacks an M.2 slot for an SSD, otherwise it would have been perfect. I did a lot of searching, and you'd be hard pressed to find another machine with a DVD-ROM that is of equivalent quality. I have no idea how the laptop will handle wear and tear, as I've only had it a week, but the build quality seems pretty good.

Example: Product Review Roll-Up

Dell Inspiron i5559-4682SLV 15.6 Inch FHD Touchscreen Sig

Reviews Analyzed: 39

Date Range: 5/5/2016 to 1/29/2017

Average Rating: 3.9

Battery ★★★★★

4.0 | | I've had this computer for 3 months already and i'm quite satisfied. the only negative comments are that 1. I' shut it off and lose some of my work. Otherwise it's a great computer. It's fast. *It has a battery life ranging from 1-1/2 hrs* minutes every day with it and it's not so much fun. The touch screen is nice as is windows 10. it's got plenty of ram and s for it.

5.0 | | This is really a fantastic computer. You will be hard-pressed to find any other computer for the price that does 1920x1080 resolution, and comes with Windows 10. *I do think the battery life could be improved, but most computers on* that was paid for it.

Display ★★★★★

5.0 | | *The laptop has a beautiful display, and was pretty responsive.* There was no crapware installed with the sys would have been perfect. I did a lot of searching, and you'd be hard pressed to find another machine with a DVD-ROM th build quality seems pretty good.

Sentiment and Rhetoric

Rhetoric is strongly related to sentiment attachment.

Those who attach opposite sentiment to an issue tend to employ different rhetoric.

Protect working families' jobs from being off-shored!!

Promote free trade for a healthy global economy!

Sentiment and Rhetoric

Rhetoric-sentiment correlation examples:

- “Pro-life” vs. “pro-choice”
- “Second Amendment” vs. “assault weapons” vs. “so-called assault weapons”
- Comments on *American Sniper*, approaching the Oscars
  - “Eastwood” vs. “Mr. Eastwood”
  - Frequent vs. infrequent mention of “terrorists”

Differences in Vocabulary: Users vs. Media

Word or phrase	Professional reviews (net negative sentiment)	User comments (net positive sentiment)	Percent difference
muslim	151	240	+ 59%
terrorist	91	176	+ 93%
death	124	213	+ 72%
hell	102	269	+164%
soldier	324	523	+ 61%
Oscar	293	84	- 71%
Siena Miller	170	28	- 84%
box office	382	72	- 81%
critic	445	167	- 62%
Mr. Eastwood	0	37	∞%

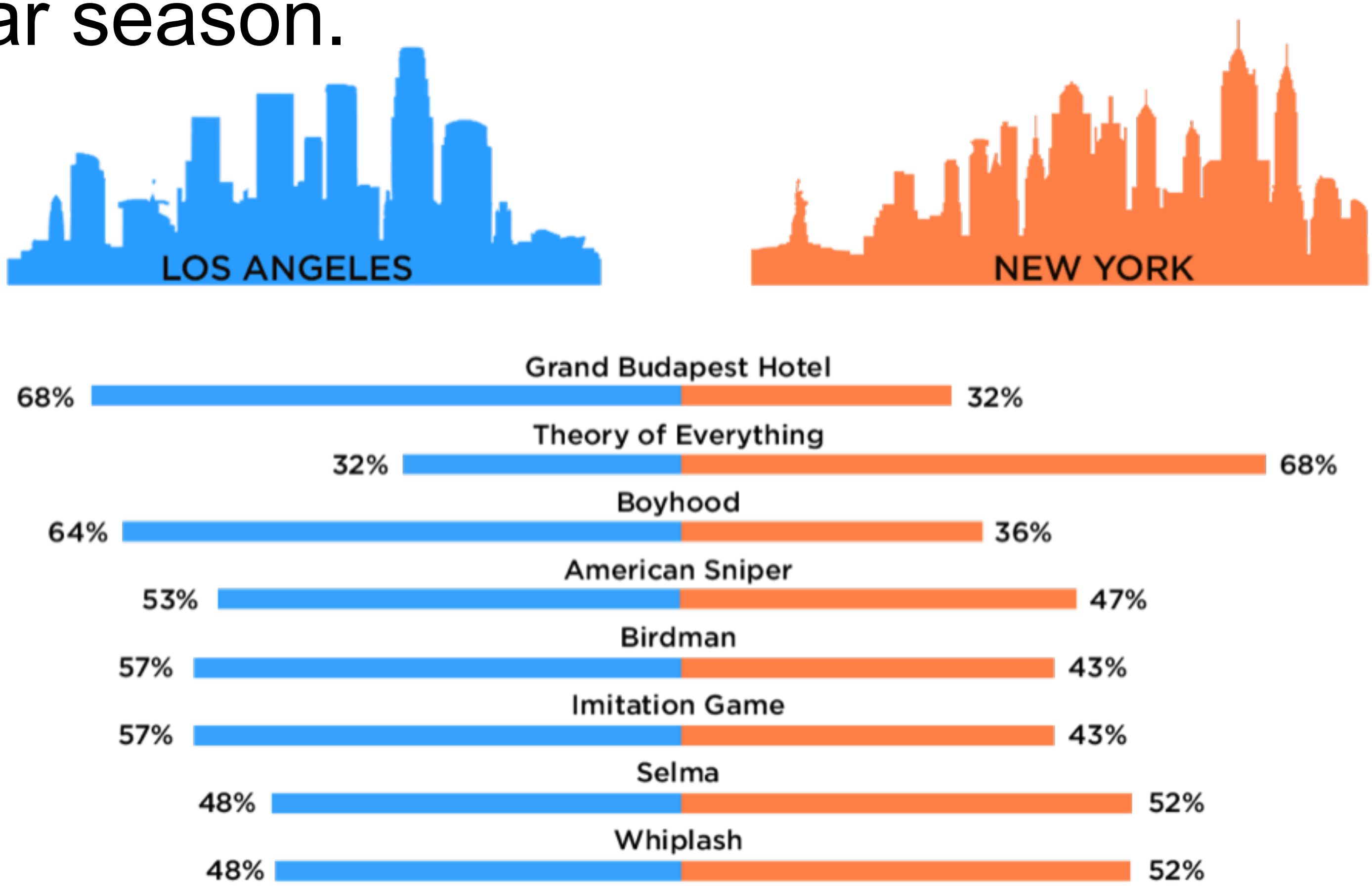
Visualization with Sentiment

Combining sentiment with demographics opens all kinds of sentiments for visualizations.

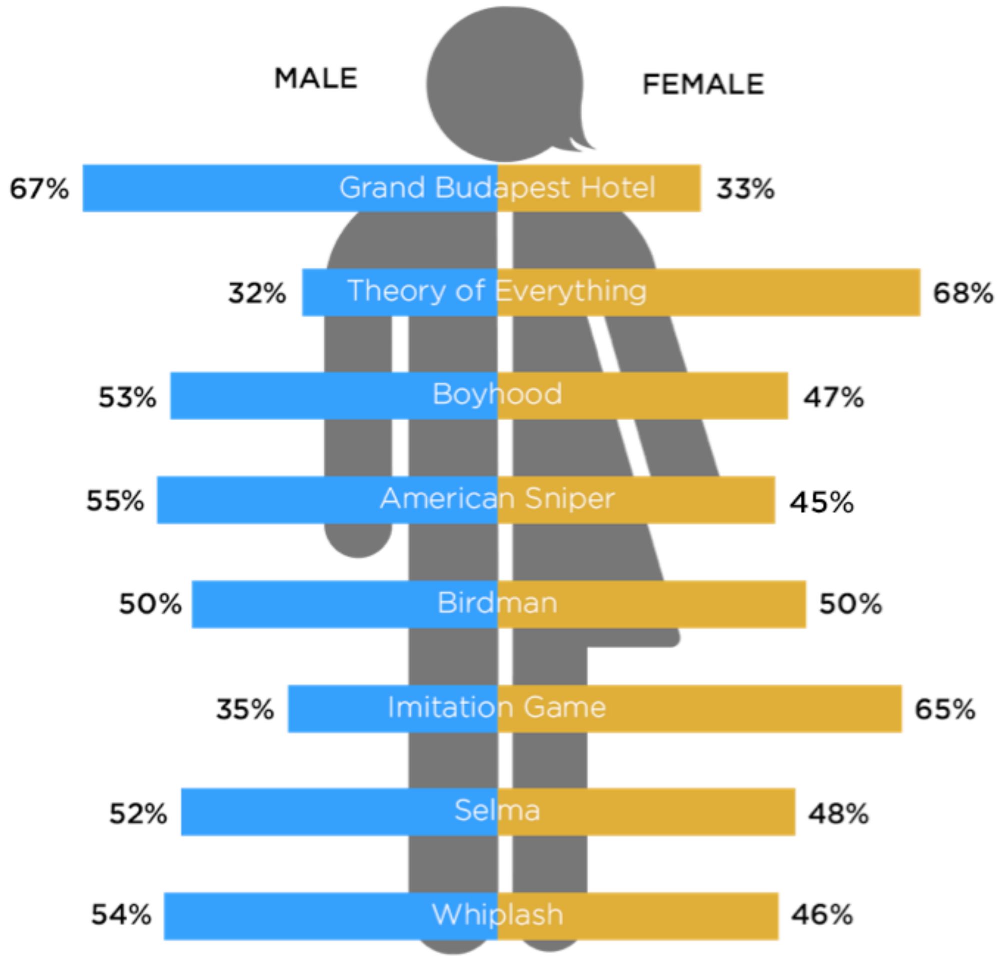
Yes, sometimes you have to draw them a picture!

Don’t Forget Geography!

User sentiment varies widely by region. Consider NY vs. LA on movies during the 2015 Oscar season.



Don’t Forget Gender!



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