

Words Can Weight

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What would the response be...?



I love you...

I like you...

Words have both meaning and weight

- “I love you”
- “I like you”
- “Dammit Janet”
- “Gosh Janet”
- “We are an innovative company”
- “We are a software company”

Review of management CATA research

❑ Journals

- 12 usual suspects (AMJ, ASQ, JAP...)

❑ Years

- 2000-2018

❑ Search criteria (18)

- Technique (“CATA”, “computerized text”, “computer-aided text”...)
- Tools (“LIWC”, “Diction”, “CAT Scanner”...)
- Process (“dictionary”, “word list”, “word count”...)

Review of management CATA research

- ❑ Initial sample: 167
- ❑ Use dictionary-based coding: 124 (74%)

- ❑ Report that weights were used... 4 (2%)
- ❑ Produce their own weights... 2 (1%)
- ❑ Document how weights were determined... 1 (0.6%)

Note: Just for dictionary-based CATA research, but I suspect a broader search of management content analysis research would yield similar numbers.

Current state of the literature

- ❑ Uniform term weighting
 - All words count equally
 - ...but should they?

- ❑ Why?
 - Institutionalized
 - Easy/convenient
 - How to weight?
 - Theory should drive methods

So how do we weight? (Manual)

- ❑ Can end up a lot like a survey
- ❑ Semantic differential: How socially oriented is the author of this text?
Prosocial | _____ | _____ | _____ | _____ | _____ | _____ | Antisocial
- ❑ Likert scale: The author of this text is socially oriented.
Strongly agree | Agree | Don't Know | Disagree | Strongly Disagree

So how do we weight?

(Dictionary-based CATA: Individual words)

- ❑ Unclear... so let's look at options

- ❑ Term Frequency-Inverse Document Frequency (TF-IDF)
 - Commonly used in Information Retrieval (e.g., Google search)
 - Words discriminate best when they:
 - Are used frequently in some texts (term frequency)
 - Are not used in all texts (inverse document frequency)

- ❑ The challenge:
 - Penalizes common-but-relevant words (“optimistic” vs “panglossian”)
 - Isn't concerned with *polarity* (“like” vs “love”)

So how do we weight? (Dictionary-based CATA: Individual words)



The screenshot shows the All Our Ideas website interface. At the top left is the logo and text "ALL OUR IDEAS". To the right are navigation links: "Cast Votes", "View Results", "About this page", and "Manage this page". The main content area features a poll question: "Which word is more reflective of authenticity?". Below the question are two blue buttons labeled "Genuine" and "Authentic". At the bottom center is a button labeled "I can't decide" with the text "0 votes on 2 ideas" underneath it.

Uses a Bayesian algorithm to assign each word a value from 0-100

Kovács et al (2013) – AllOurIdeas.org

So how do we weight?

(Dictionary-based CATA: Individual words)

Kovács, Carroll, and Lehman: *Authenticity and Consumer Value Ratings*
 Organization Science 25(2), pp. 458–478, © 2014 INFORMS

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Table 1 Authenticity Scores Assigned to Keywords

Keyword	Score	Keyword	Score	Keyword	Score	Keyword	Score
Authentic	95	Truthful ^a	68	Usual	53	Bogus	13
Genuine	92	Unmistakable ^a	68	Decent ^a	51	Forgery	13
Real	88	Artisan ^a	67	Unusual	51	Fake	12
Skilled ^a	83	Unpretentious ^a	67	Caring ^a	49	Hoax	11
Faithful	81	Heartful ^a	66	Ambitious ^a	48	Cheat	10
Legitimate ^a	81	Delicious	65	Replica ^a	46	Dishonest	10
Original ^a	80	Virtuous	64	Offbeat	43	Feigned	10
Traditional	79	Normal ^a	63	Atypical	41	Ersatz	9
Pure	78	Creative ^a	62	Unassuming ^a	37	Faked	9
Historical ^a	77	Interesting ^a	62	Invented	36	Imitation	9
Sincere	77	Orthodox ^a	62	New ^a	36	Quack	9
Master chef	75	Artful ^a	60	Unconventional	36	Unreal	8
Craftsmanship	74	Special ^a	60	Peculiar	35	Humbug	7
Honest ^a	74	Righteous	58	Outlandish	32	Impostor	7
Integrity ^a	74	Substantial ^a	57	Assumed	30	Sham	7
Quintessential	74	Authoritative	56	Idiosyncratic	30	Unauthentic	7
Expert	73	Typical	56	Quirky	29	Deceptive	6
Iconic ^a	73	Awesome ^a	55	Extroverted ^a	28	Inauthentic	6
Inspiring ^a	73	Moral	55	Modern	27	False	6
Unique ^a	72	Eccentric	54	Unorthodox ^a	27	Phony	5
Wholesome	72	Ethical ^a	54	Pretentious	19	Scam	4
Professional	70	Fresh ^a	53	Untraditional ^a	17		
Skillful	70	Old-fashioned ^a	53	Artificial	14		

^aKeywords added by participants.

So how do we weight?

(Dictionary-based CATA: Entire dictionaries)

Table 1. Ten Most Important Linguistic Features in Measuring Extraversion

Linguistic feature	Source	Description	Relation with extraversion	Weights
Unique	LIWC	Measure of repetition of words in a given text.	-	.6457
MEANP	MRC	Paivio meaningfulness, defined as the mean value of written associations people list with a word in 30 seconds. (Paivio, 1968)	+	.3553
We	LIWC	The relative number of times the first-person plural is used, e.g., "we," "us," "our" (11 words).	+	.2845
T-L-FREQ	MRC	Measure of how frequently words are used in the English language. (Thorndike and Lorge, 1944)	-	.2544
Number	LIWC	The relative frequency of numbers in the text, e.g., "one," "thirty," "million" (29 words).	-	.2468
Motion	LIWC	The relative frequency of words related to motion in the text, e.g., "walk," "move," "go" (73 words).	+	.2464
Insight	LIWC	The relative frequency of words related to insight, e.g., "think," "know," "consider" (116 words).	-	.2355
Up	LIWC	The relative frequency of words like "up," "above," "over" (12 words).	-	.2296
NLET	MRC	Average number of letters in a word.	-	.2282
WPS	LIWC	Average number of words per sentence.	+	.2219

Uses Machine Learning to assign weights to Dictionary results

Malhotra et al (2018) citing Mairesse et al (2007)

Project In-Progress (Alphabetical)



Jason Kiley



Tim Michaelis



Clay Posey

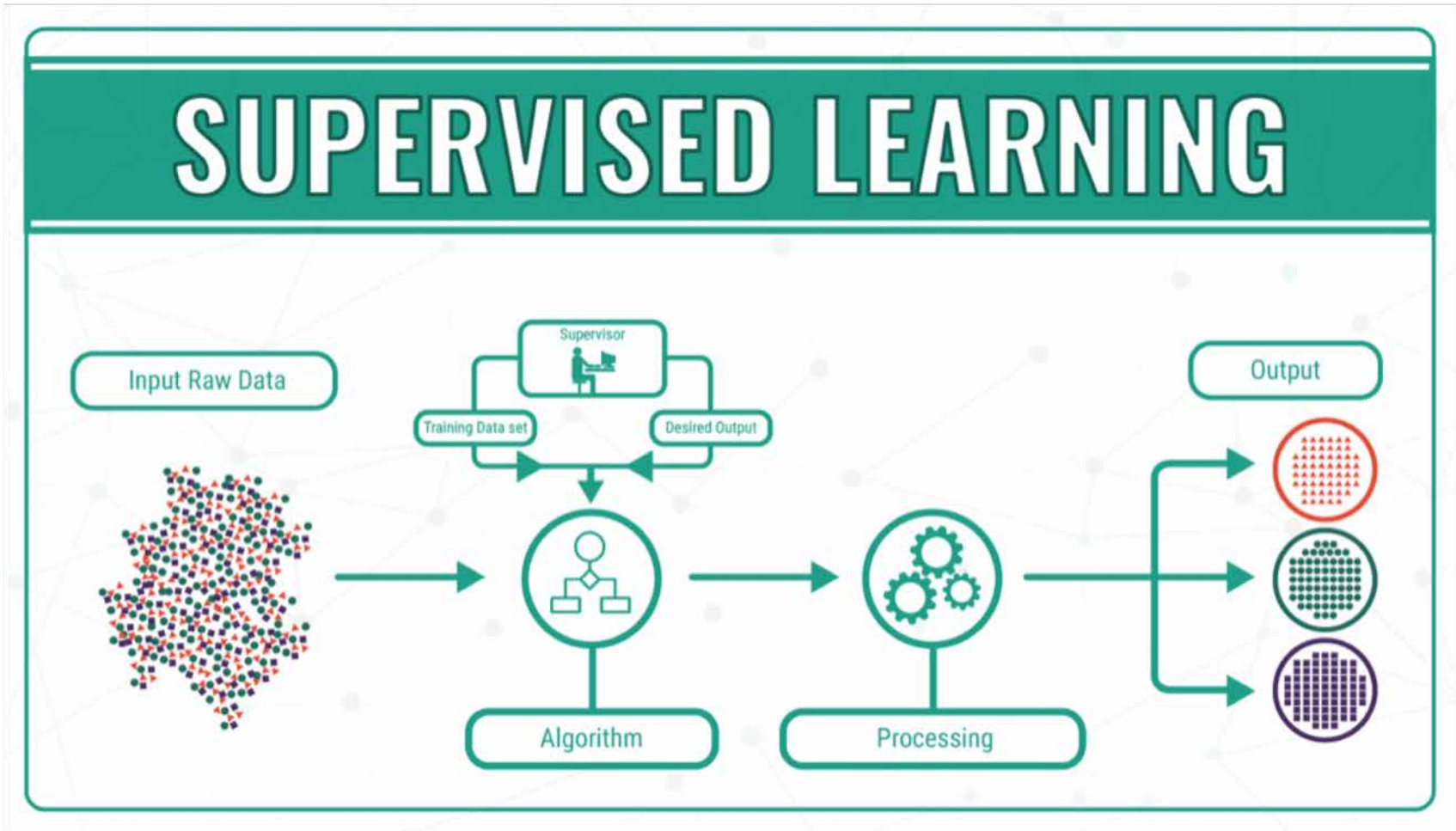
Project In-Progress

- ❑ Comparison of term weighting approaches

- ❑ Existing approaches
 - Unweighted
 - TF-IDF
 - AllOurIdeas.org

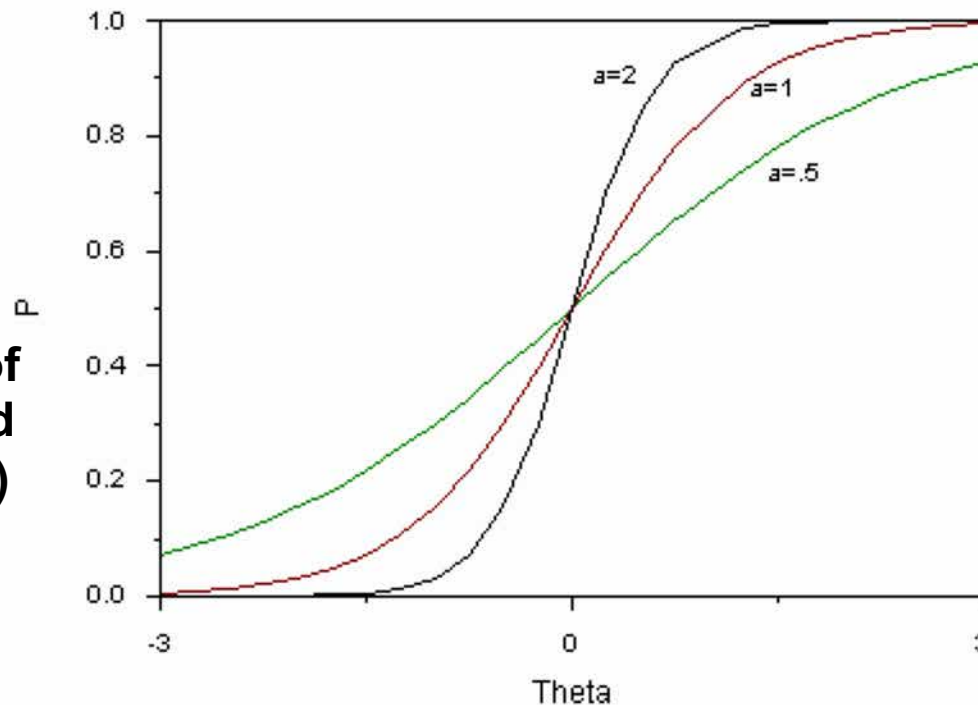
- ❑ New approaches
 - Machine Learning
 - Item Response Theory

Machine Learning



Item Response Theory: Discrimination

a parameter

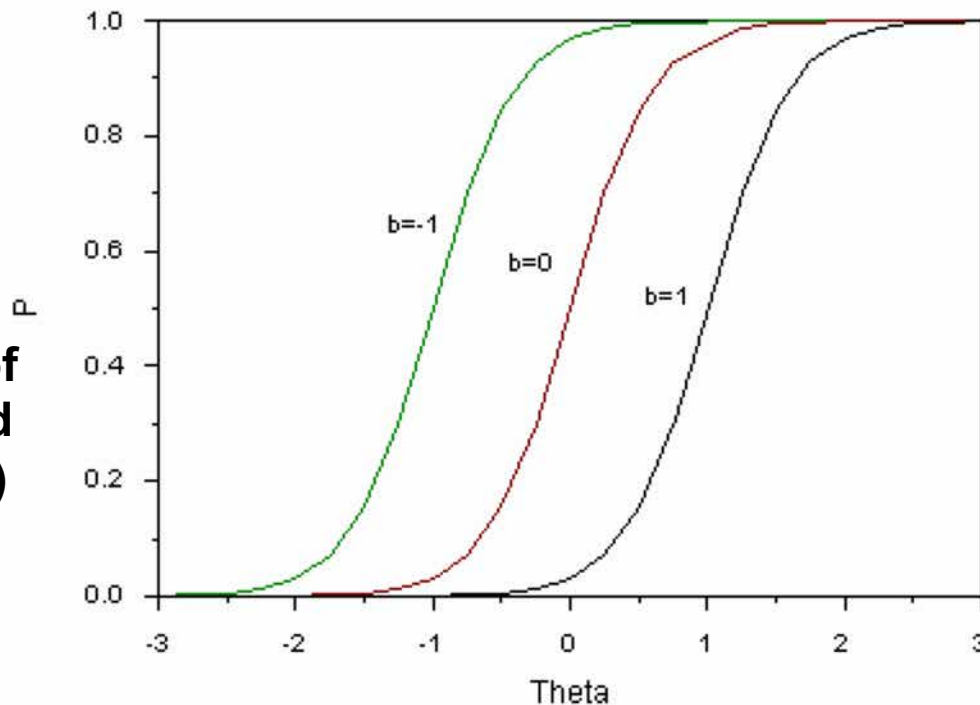


Probability of
using a word
(e.g., “love”)

Your “true” score
(e.g., positive affect)

Item Response Theory: Difficulty

The b parameter



Probability of
using a word
(e.g., “love”)

Your “true” score
(e.g., positive affect)

Questions?

