Information Retrieval

INFO 4300 / CS 4300

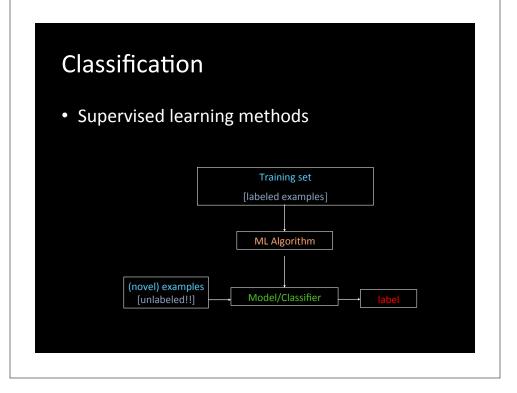
- Last class
 - Indexing
- » Index construction
- » Compression
- » Ranking model
- Today
 - (Fun) detour in honor of Fall Break
 - » Text classification
 - » Opinion spam detection
 - Marseille video: cs4740 class favorite

Classification

- Classification is the task of automatically applying labels to items
- Useful for many search-related tasks
 - Spam detection
 - Email categorization
 - Sentiment classification
 - Language identification
 - Online advertising

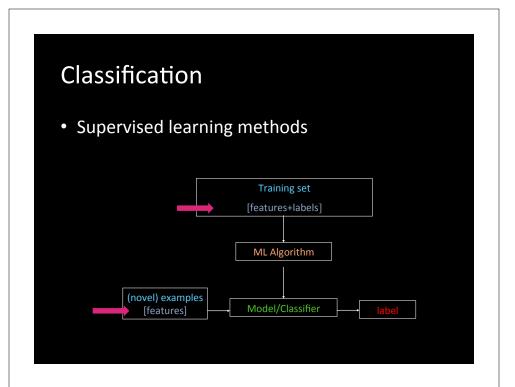
Classification

- Classification is a classical pattern recognition / machine learning problem
 - Asks "what class does this item belong to?"
 - Supervised learning task
- Items can be documents, queries, emails, entities, images, etc.



How to Classify?

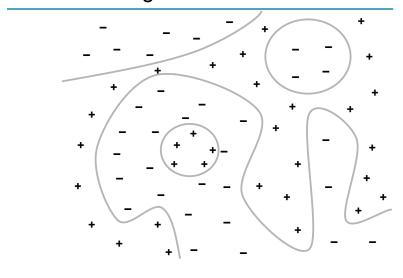
- How do humans classify items?
- For example, suppose you had to classify the "healthiness" of a food
 - Identify set of *features* indicative of health
 » fat, cholesterol, sugar, sodium, etc.
 - Extract features from foods
 - » Read nutritional facts, chemical analysis, etc.
 - **Combine evidence** from the features into a hypothesis
 - » Add health features together to get "healthiness factor"
 - Finally, classify the item based on the evidence
 - » If "healthiness factor" is above a certain value, then deem it healthy



Ontologies

- Ontology is a labeling or categorization scheme
- Examples
 - Binary (spam, not spam)
 - Multi-valued (red, green, blue)
 - Hierarchical (news/local/sports)
- Different classification tasks require different ontologies

Nearest Neighbor Classification



Information Retrieval

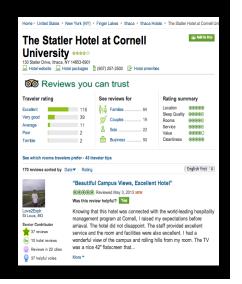
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Online Reviews

- Consumers increasingly rate, review and research products online
- Potential for opinion spam
 - Disruptive opinion spam
 - Deceptive opinion spam

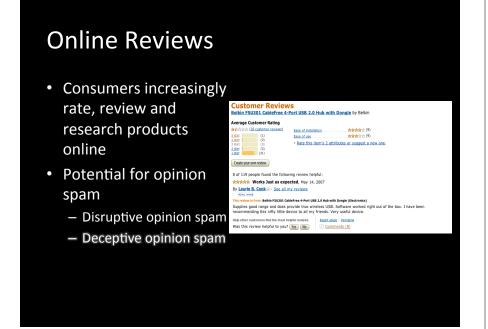
Ott, Cardie & Hancock [ACL 2011, WWW 2012, NAACL 2013, ACL 2013]

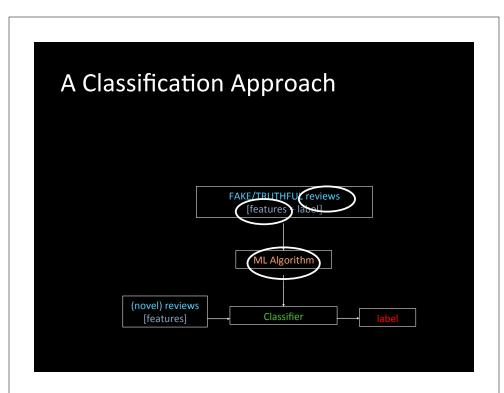


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Which of these two hotel reviews is *deceptive* opinion spam?

Which of these two hotel reviews is *deceptive* opinion spam?

Date of review: Jun 9, 2006

4 people found this review helpful

I have stayed at many hotels traveling for both business and pleasure and I can honestly say that The James is tops. The service at the hotel is first class. The rooms are modern and very comfortable. The location is perfect within walking distance to all of the great sights and reestaurants. Highly recommend to both business travellers and couples.

This review is the subjective opinion of a TripAdvisor member and not of TripAdvisor LLC.

View profile | Send message | Compliment reviewer Report problem with review Date of review: Jun 9, 2006

4 people found this review helpful

My husband and I stayed at the James Chicago Hotel for our anniversary. This place is fantastic! We knew as soon as we arrived we made the right choice! The rooms are BEAUTIFUL and the staff very attentive and wonderful!! The area of the hotel is great, since! love to shop I couldn't ask for more!! We will definatly be back to Chicago and we will for sure be back to the James Chicago.

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View profile | Send message | Compliment reviewer Report problem with review Which of these two hotel reviews is *deceptive* opinion spam?

Answer:

Date of review: Jun 9, 2006

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View profile | Send message | Compliment reviewer

Report problem with review

Previous Work

- Jindal & Liu (2008)
 - Opinion spam is different from e-mail or Web spam
 - No gold standard deceptive reviews
 - Identify *duplicate* vs. *non-duplicate* reviews
- Mihalcea & Strapparava (2009), Zhou et al. (2004, 2008)
 - N-gram-based features, small corpora
- Different deception tasks

ACL (2011), WWW (2012)

Overview

- Motivation and Background
- Gathering Data
- Human Performance
- Classifier Construction and Performance

Data: Deceptive Reviews

- Label existing reviews
 - Can't manually do this
 - Duplicate detection (Jindal and Liu, 2008)
- Create new reviews
 - Mechanical Turk

Data

- Mechanical Turk
 - Have: 20 chosen hotels
 - Want: 20 deceptive positive reviews / hotel
 - Offer: \$1 / reviewGet: 400 reviews

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Data

- Mechanical Turk
 - Have: 20 chosen hotels
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Instructions

Assume that you work for the hotel's marketing department, and pretend that your boss wants you to write a fake review (as if you were a customer) to be posted on a travel review website; additionally, the review needs to sound realistic and portray the hotel in a positive light.

Data

- Allow only a single submission per Turker
- Restrict our task to Turkers
 - Who are located in the United States
 - Who maintain an approval rating of at least 90%
- Check for plagiarism

Data: Truthful Reviews

- Mine all TripAdvisor.com reviews
 - From the 20 most-reviewed Chicago hotels (6,977)
 - Discard non-5-star reviews (3,130)
 - Exclude reviews written by first-time reviewers (1,607), under 150 characters, non-English. 2124 reviews left.
- Select 400 reviews such that the lengths are distributed similarly to the deceptive reviews

Validating the Deceptive Reviews

- Measure human performance
- Can also serve as a baseline

Human Performance

			T	RUTHFU	JL	DI	ECEPTIV	/E
		Accuracy	P	\mathbf{R}	\mathbf{F}	P	\mathbf{R}	F
	JUDGE 1	61.9%	57.9	87.5	69.7	74.4	36.3	48.7
HUMAN	JUDGE 2	56.9%	53.9	95.0	68.8	78.9	18.8	30.3
	JUDGE 3	53.1%	52.3	70.0	59.9	54.7	36.3	43.6

- 80 truthful and 80 deceptive reviews
- 3 undergraduate judges
 - Truth bias

Human Performance

	ormed at chance o-value = 0.1)	2	Т	RUTHFU	JL	Di	ECEPTI	VE
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Performed at chance (p-value = 0.5)

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Human Performance

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• 80 truthful and 80 deceptive reviews Classified fewer than 12% of opinions as deceptive!

opinions as deceptive!

- 3 undergraduate judges
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Overview

- Motivation and Background
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Classifier

• Linear SVM (Support Vector Machine)

Feature representation

- Three feature sets encode potentially complementary framings
 - Problem in genre identification
 - Instance of psycholinguistic deception detection
 - Standard text categorization

Features: genre identification

- 48 part-of-speech (PoS) features
- Expectations
 - Truth similar to informative writing
 - Deception similar to imaginative writing

Performance

				T	RUTHFU	JL	DI	ECEPTIV	/E
Approach		Features	Accuracy	P	R	F	P	R	F
GENRE IDENTIFICAT	ΓΙΟΝ	POS	73.0%	75.3	68.5	71.7	71.1	77.5	74.2
Oı	utperi p-va	forms human judg lues = {0.06, 0.01, 0.001}	ges!						

Analysis

TRUTH	FUL/INFORMATIVE		DECEPT	IVE/IMAGINATIVE	
Category	Variant	Weight	Category	Variant	Weight
	Singular	0.008		Base	-0.057
NOUNS	Plural	0.002		Past tense	0.041
NOUNS	Proper, singular	-0.041		Present participle	-0.089
	Proper, plural	0.091	VERBS	Singular, present	-0.031
	General	0.002		Third person	0.026
ADJECTIVES	Comparative	0.058		singular, present	0.020
	Superlative	-0.164		Modal	-0.063
PREPOSITIONS	General	0.064	VERBS	General	0.001
DETERMINERS	General	0.009	W EUP?	Comparative	-0.035
COORD. CONJ.	General	0.094	PRONOUNS	Personal	-0.098
VERBS	Past participle	0.053	PRONOUNS	essive	-0.303
ADVERBS	Superlative	-0.094	PRE-DETERMINERS	Gener	0.017

e.g., least often

- POS feature analysis
 - superlatives

e.g., fastest, nicest

Features: psycholinguistic

- Linguistic Inquiry and Word Count (Pennebaker et al., 2007)
 - Counts instances of ~4,500 keywords
 - Regular expressions, actually
 - Keywords are divided into 80 dimensions across
 4 broad groups

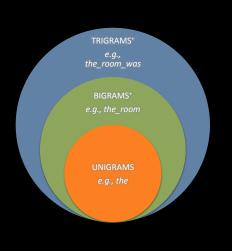
Features: psycholinguistic

- Linguistic processes
 - e.g., average number of words per sentence
- Psychological processes
 - e.g., talk, happy, know, feeling, eat
- Personal concerns
 - e.g., job, cook, family
- Spoken categories
 - e.g., yes, umm, blah

Performance TRUTHFUL DECEPTIVE R Approach Features Accuracy \mathbf{P} \mathbf{R} \mathbf{F} 73.0% 77.5 75.3 68.5 71.7 71.1 74.2 GENRE IDENTIFICATION POS PSYCHOLINGUISTIC 76.8%77.276.676.477.5LIWC 76.076.9DECEPTION DETECTION **Outperforms PoS** p-value = 0.02

Features: text categorization

- Features
 - n-grams



Performance

			T	RUTHFU	JL	DI	ECEPTIV	Æ
Approach	Features	Accuracy	P	R	F	P	R	F
GENRE IDENTIFICATION	POS	73.0%	75.3	68.5	71.7	71.1	77.5	74.2
PSYCHOLINGUISTIC	LIWC	76.8%	77.2	76.0	76.6	76.4	77.5	76.9
DECEPTION DETECTION	LIWC	10.070	11.2	10.0	10.0	10.4	11.0	10.9
	UNIGRAMS	88.4%	89.9	86.5	88.2	87.0	90.3	88.6
TEXT CATEGORIZATION	BIGRAMS	89.6	90.1	89.0	89.6	89.1	90.3	89.7
TEXT CATEGORIZATION	LIWC+BIGRAMS	89.8	89.8	89.8	89.8	89.8	89.8	89.8
	TRIGRAMS	89.0%	89.0	89.0	89.0	89.0	89.0	89.0

Outperform all other methods

Analysis

- LIWC+BIGRAMS feature analysis
 - Spatial difficulties (Vrij et al., 2009)
 - Psychological distancing (Newman et al., 2003)

	T mrd D	ICD AMG
	LIWC+B	IGRAMS
	TRUTHFUL	DECEPTIVE
		chicago
		my
	on	hotel
\Rightarrow	location	$_{,_}$ and
		luxury
	$allpunct_{LIWC}$	experience
\Rightarrow	floor	hilton
		business
	the_hotel	vacation
	bathroom	
	small	spa
	helpful	looking
	\$	while
	hotel	husband
	other	$my_husband$

Analysis

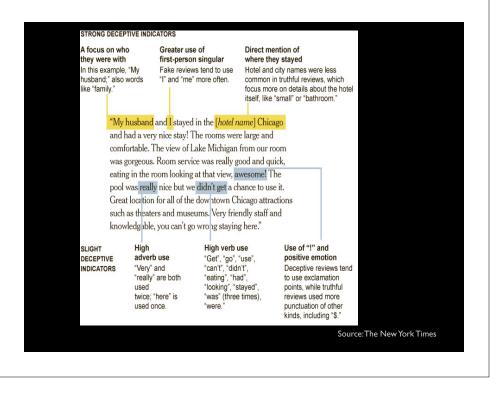
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LIWCIE	
TIMC±E	IGRAMS
TRUTHFUL	DECEPTIVE
-	chicago
	my
on	hotel
location	,_and
	luxury
$\operatorname{allpunct}_{\operatorname{LIWC}}$	experience
floor	hilton
	business
the_hotel	vacation
bathroom	
small	spa
helpful	looking
\$	while
$hotel_{-}$.	husband
other	$my_husband ext{ } $

Analysis

- LIWC+BIGRAMS feature analysis
 - Spatial difficulties (Vrij et al., 2009)
 - Psychological distancing (Newman et al., 2003)





Conclusions

- People are not good at detecting fake on-line reviews
- Developed automated classifier capable of nearly 90% accuracy when detecting (this one type of!) deceptive opinion spam



reviews from our community

www.reviewskeptic.com



Follow-up and Ongoing Work

- Prevalence of opinions [www 2012]
- Negative opinions [NAACL 2013]
- Other domains (e.g., restaurants, doctors)
- Vary context of deception (e.g., domain experts vs. turkers)
- Countermeasures