

Listen

discern intent, to target the right message

.....recognize a shopper from a browser

..... gauge opinion and sentiment

..... understand what people are saying

measuring *information* ... what is “news”?

why did they do this?

so that *you* read the story!

“dog bites man” – not news

“man bites dog” – interesting!

why?

“The In _____ res Gleick, 2011

The New York Times

Europe

WORLD	U.S.	N.Y. / REGION	BUSINESS	TECHNOLOGY	SCIENCE	HEALTH	SPORTS	OPINION
AFRICA	AMERICAS	ASIA PACIFIC	EUROPE	MIDDLE EAST				

At British Inquiry, Murdoch Apologizes Over Scandal

By ALAN COWELL
Published: April 26, 2012

LONDON — After a day of testimony at a British judicial inquiry over his ties, friendships and disputes with British politicians, [Rupert Murdoch](#) returned to the witness stand on Thursday, saying he apologized for failing to take measures to avert the [hacking scandal](#) that has convulsed his media outpost here.

FACEBOOK
TWITTER
GOOGLE+
E-MAIL
SHARE

Claude Shannon (1948): *information* is related to surprise

a message informing us of an event that has probability p conveys

$-\log_2 p$ bits of *information* $-\log .5 = 1$

A • • • •
B • • • •
C • • • •
D • • • •
E • • • •
F • • • •
G • • • •
H • • • •
I • • • •
J • • • •

a, in, the, ..
information
miscellaneous

“It from bit” John Wheeler, 1990

when we pick up a newspaper, we are looking for maximum

information, so more ‘surprising’ events make for better news!

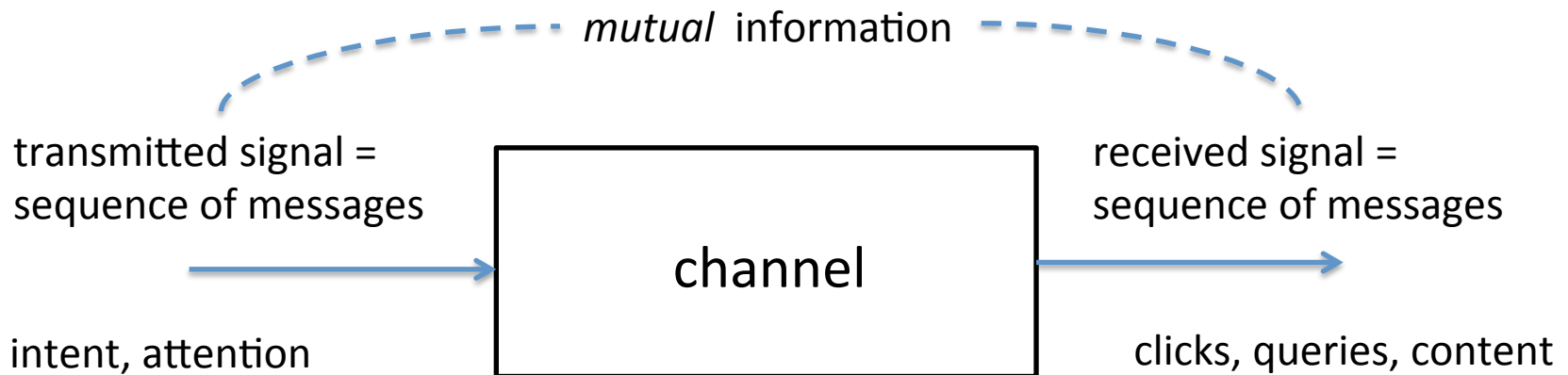
in passing, you glance at some ads, and the paper makes money!

information and online advertising

when to place an ad, and *where* to place an ad?

what if the interesting news is on the sports page?

communication along a noisy channel (Shannon):



advertising model



AdSense, keywords and mutual information

advertisers bid for keywords in Google's online auction

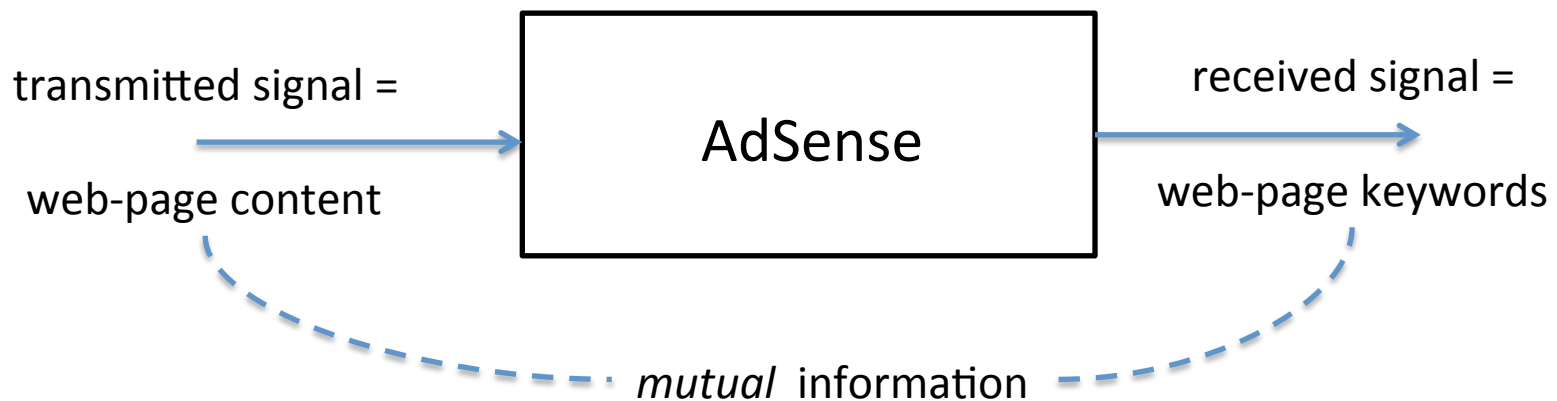
highest bidders' ads placed against matching searches

➤ increases *mutual information* between ad \$s and sales..

Google's AdSense places ads in *other* web-pages as well

which keyword-bids should get ad-space on a page?

(`inverse-search': pages to keywords vs. query words to pages)



➤ how to maximize the mutual information?

TF-IDF

clearly, a word like 'the' conveys much less about the content of a page on computer science than say 'Turing'

rarer words make better keywords

IDF = inverse document frequency of word $w = \log_2 \frac{N}{N_w}$
(N total documents, with N_w containing w)

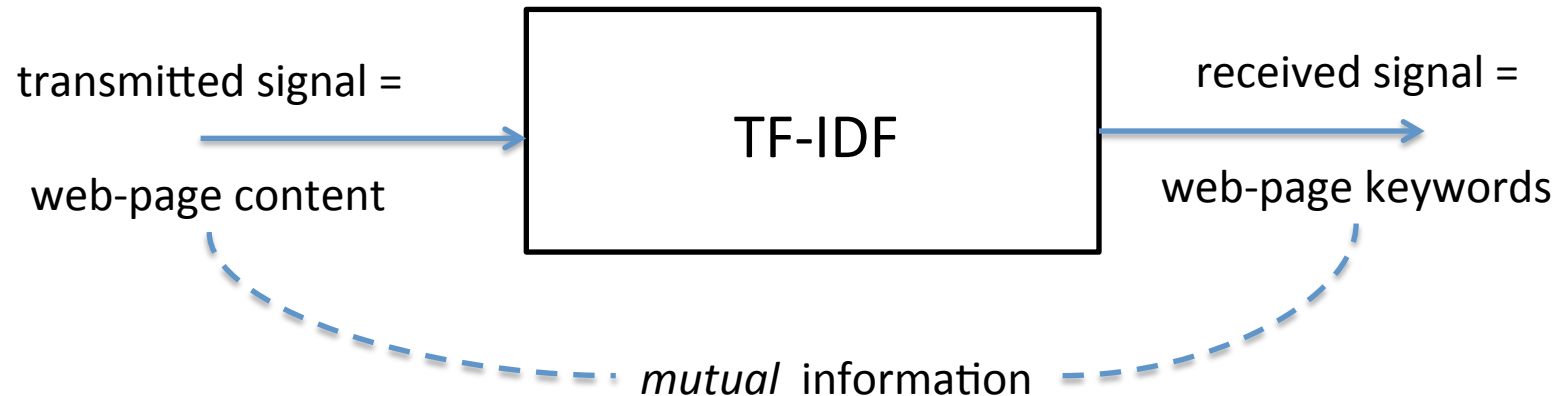
a document that contains 'Turing' 15 times is more likely about computer science than one with 2 occurrences

more frequent words make better keywords

if n_w^d = frequency of w in document d

TF-IDF = term-frequency x IDF = $n_w^d \log_2 \frac{N}{N_w}$

TF-IDF and mutual information



TF-IDF was invented as a *heuristic* technique

However it has been shown that the mutual information

between *all-pages* and *all-words* is prop. to $\sum_d \sum_w n_w^d \log_2 \frac{N}{N_w}$

“An information-theoretic perspective of TF-IDF measures”, Kiko Aizawa, Journal of Information Processing and Management, Volume 39 (1), 2003

keyword summarization: TF-IDF + web

TF – from text
where to get IDF?

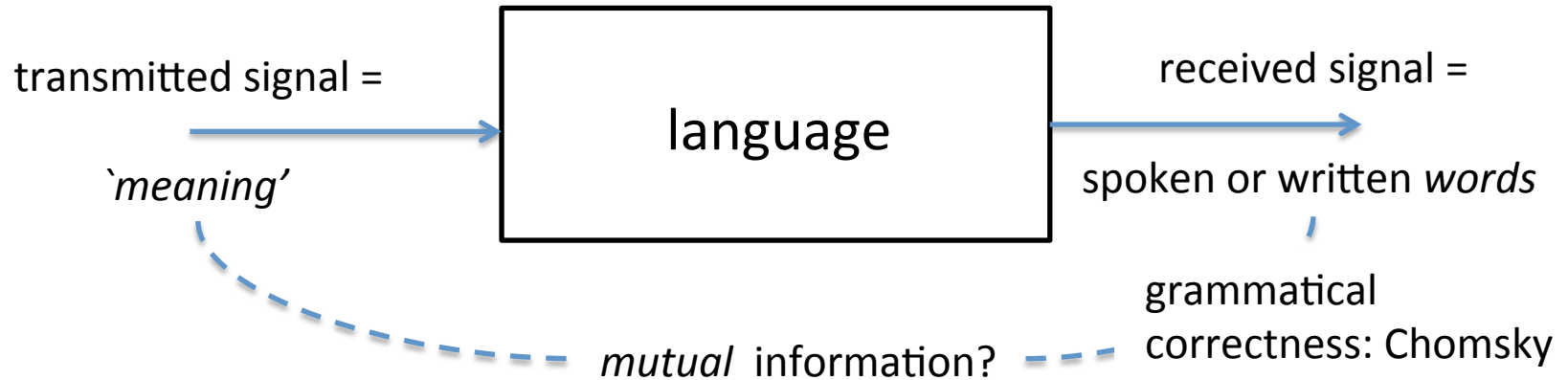
web!

The course is about building 'web-intelligence' applications exploiting big data sources arising social media, mobile devices and sensors, using new big-data platforms based on the 'map-reduce' parallel programming paradigm. The course is being offered ..

word	hits	IDF	TF	TF-IDF
the	25 B	$50 / 25 = 2$	2	2
course	2 B	$50 / 2 = 25$	2	9.2
media	7 B	$50 / 7 = 7$	1	2.8
map-reduce	0.2 B	$50 / .2 = 250$	1	7.9
web-intelligence	0.3 B	$50 / .3 = 166$	1	7.3

so the top keywords can be easily *computed*
what about choosing among these for a good *title*? ...

language and *information*



language is highly *redundant*: 75% redundancy in English: Shannon
“the lamp was on the d...” – you can easily guess what’s next

language tries to maintain ‘uniform information density’

“Speaking Rationally: Uniform Information Density as an Optimal Strategy for Language Production”, Frank A, Jaeger TF, 30th Annual Meeting of the Cognitive Science Society 2008

language and *statistics*

imagine yourself at a party -

- snippets of conversation; which ones catch your interest?

a 'web intelligence' program tapping Twitter, Facebook or Gmail

- what are people talking about; who have similar interests ...

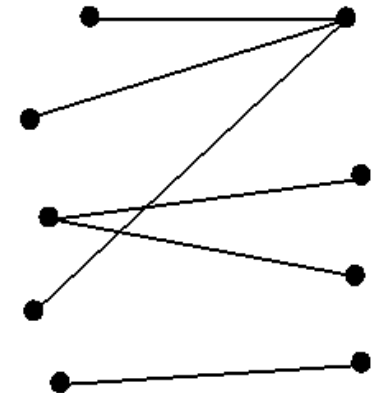
“similar documents have similar TF-IDF keywords” ??

- e.g. 'river' , 'bank' , 'account' , 'boat' , 'sand' , 'deposit' , ...
- *semantics* of a word-use depend on context ... *computable* ?
- do similar keywords co-occur in the same document?
- what if we *iterate* ... in the bi-partite graph:

➤ latent semantics / topic models / ... vision

is semantics – i.e., meaning, just statistics?

what about intent?



machine learning: surfing or shopping?

keywords: *flower, red, gift, cheap*;

- should ads be shown or not? - *are you a surfer or a shopper?*

machine learning is all about learning from past data

- past behavior of many *many* searchers using these keywords:

R	F	G	C	Buy?
n	n	y	y	y
y	n	n	y	y
y	y	y	n	n
y	y	y	n	y
y	y	y	n	n
y	y	y	y	n
.....				
.....				

prediction using conditional probability

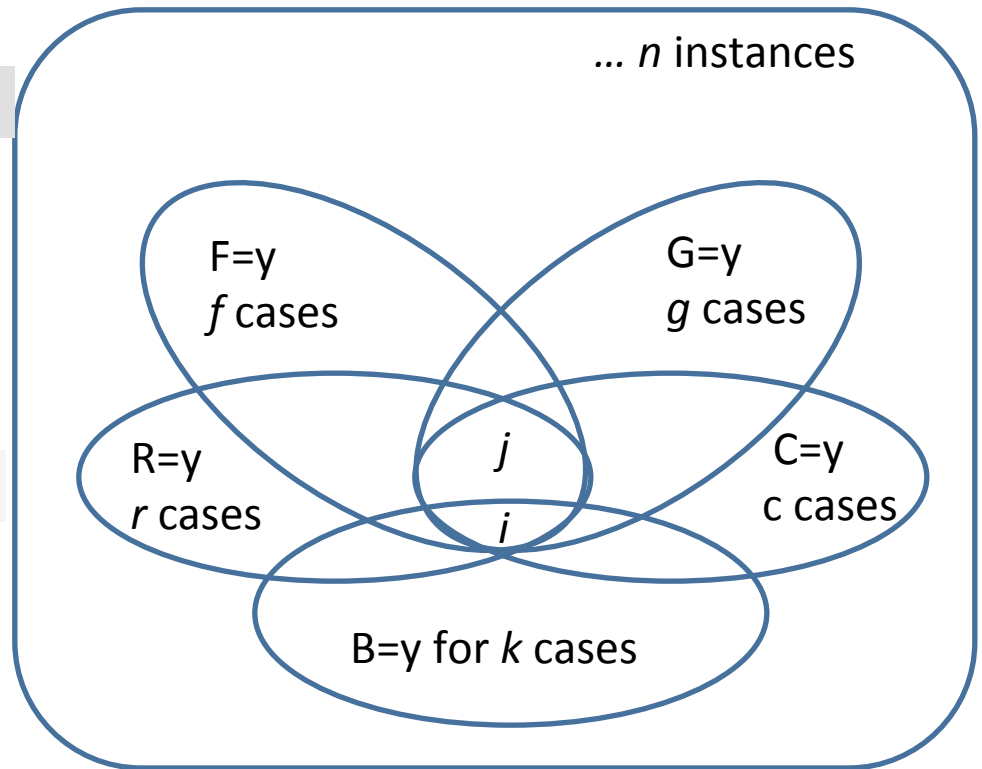
we want to determine $P(B)$, given R, F, G, C

in other words, $P(B | R, F, G, C)$ – *conditional* probability

R	F	G	C	B
y	y	y	y	y
n	y	y	y	y
n	n	y	y	y
n	n	n	y	y
.....				
y	y	y	y	n
n	y	y	y	n
n	n	y	y	n
.....				

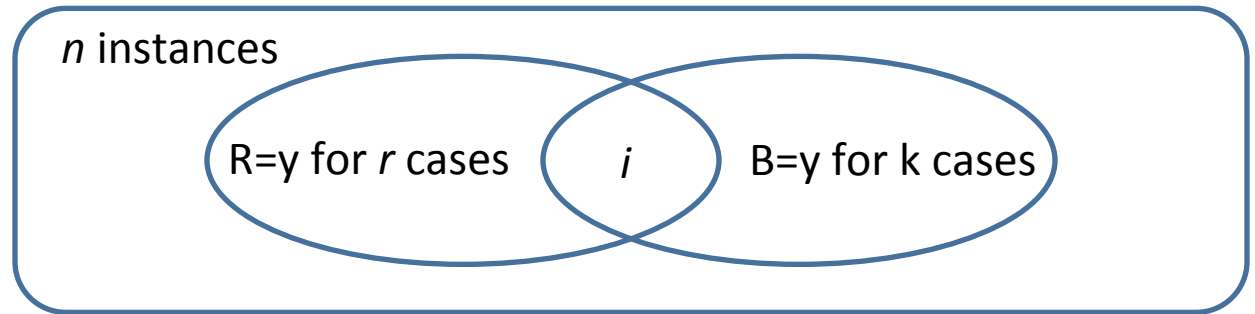
$$(i/n)^*(n/|R \vee F \vee G \vee C|)$$

$$(j/n)^*(n/|R \vee F \vee G \vee C|)$$



sets, frequencies and Bayes rule

#	R	B
1	y	y
2	n	n
3	y	n



probability $p(B | R) = i/r$

probability $p(R) = r/n$

probability $p(R \text{ and } B) = i/n = (i/r) * (r/n)$

so $p(B, R) = p(B | R) p(R)$

this is Bayes rule:

$$P(B, R) = P(B | R) P(R) = P(R | B) P(B) [= (i/k) * (k/n)]$$

independence

statistics of R do not depend on C and vice versa

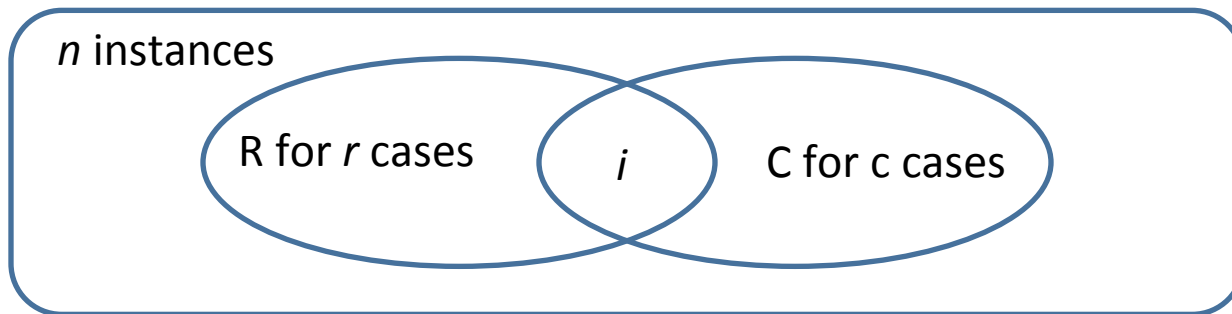
$$P(R) = r/n, P(C) = c/n$$

$$P(R|C) = i/c, P(C|R) = i/r$$

R and C are independent if and only if

$$i/c = r/n \quad \equiv \quad i/r = c/n$$

$$\text{or } P(R|C) = P(R) \quad \equiv \quad P(C|R) = P(C)$$



“naïve” Bayesian classifier

assumption – R and C are independent *given* B

$$\begin{aligned} P(B | R, C) * P(R, C) &= P(R, C | B) * P(B) \text{ (Bayes rule)} \\ &= \underline{P(R | C, B) * P(C | B)} * P(B) \text{ (Bayes rule)} \\ &= \underline{P(R | B)} * P(C | B) * P(B) \text{ (independence)} \end{aligned}$$

so, given values r and c for R and C

compute:

$$\frac{p(r | B=y) * p(c | B=y) * p(B=y)}{p(r | B=n) * p(c | B=n) * p(B=n)}$$

choose B=y if this is $> \alpha$ (usually 1), and B=n otherwise

‘NBC’ works the same for N features

for example, 4 features R, F, G, C ..., and in general

N features, $X_1 \dots X_N$, taking values $x_1 \dots x_N$

compute the *likelihood ratio*

$$L = \prod_{i=1}^N \frac{p(x_i | B=y)}{p(x_i | B=n)} * \frac{p(B=y)}{p(B=n)}$$

and choose $B=y$ if $L > \alpha$ and $B=n$ otherwise

normally we take logarithms to make multiplications into additions, so you would frequently hear the term “*log-likelihood*”

sentiment analysis via machine learning

100s of millions of Tweets per day:

can listen to “the voice of the consumer” like never before

sentiment – brand / competitive position ... +/- counts

count		Sentiment
2000	I really like this course and am learning a lot	positive
800	I really hate this course and think it is a waste of time	negative
200	The course is really too simple and quite a bore	negative
3000	The course is simple , fun and <i>very</i> easy to follow	positive
1000	I’m enjoying this course a lot and learning something too	positive
400	I would enjoy myself a lot <i>if</i> I did <i>not</i> have to be in this course	negative
600	I did <i>not</i> enjoy this course enough	negative

$$p(+)=6000/8000=.75; p(-)=2000/8000=.25$$

$$p(\text{like}|+)=2000/6000=.33; p(\text{enjoy}|+)=.16; \dots \underline{p(\text{hate}|+)=1/6000=.0002} \dots$$

$$p(\text{hate}|-)=800/2000=.4; p(\text{bore}|-)=.1; p(\text{like}|-)=1/2000=.0001;$$

$$\text{also } \dots \underline{p(\text{enjoy}|-)=1000/2000=.5} ! \text{ and while } p(\text{lot}|+)=.5, \underline{p(\text{lot}|-)=.4} !$$

smoothing

Bayesian sentiment analysis (cont.)

positive likelihoods	negative likelihoods
$p(\text{like} +) = .33$	$p(\text{like} -) = .0001$
$p(\text{lot} +) = .5$	$p(\text{lot} -) = .4$
$p(\text{hate} +) = .0002$	$p(\text{hate} -) = .4$
$p(\text{waste} +) = .0002$	$p(\text{waste} -) = .4$
$p(\text{simple} +) = .5$	$p(\text{simple} -) = .1$
$p(\text{easy} +) = .5$	$p(\text{easy} -) = .0001$
$p(\text{enjoy} +) = .16$	$p(\text{enjoy} -) = .5$

now faced with a *new* tweet:
compute the *likelihood ratio*:

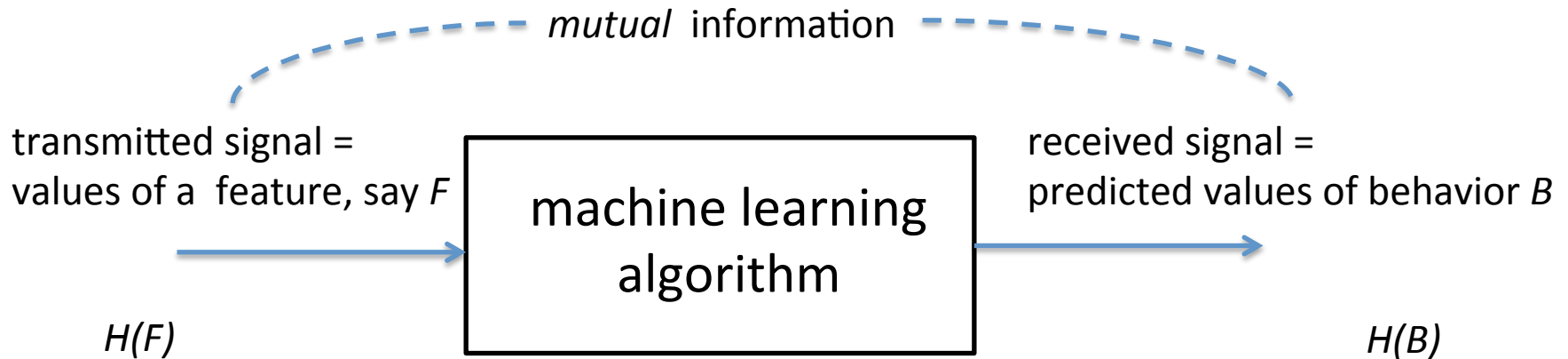
I really **like** this **simple** course a **lot**

$$L = \frac{p(\text{like} | +)p(\text{lot} | +)[1 - p(\text{hate} | +)][1 - p(\text{waste} | +)]p(\text{simple} | +)[1 - p(\text{easy} | +)][1 - p(\text{enjoy} | +)]p(+)}{p(\text{like} | -)p(\text{lot} | -)[1 - p(\text{hate} | -)][1 - p(\text{waste} | -)]p(\text{simple} | -)[1 - p(\text{easy} | -)][1 - p(\text{enjoy} | -)]p(-)}$$

we get $L = \frac{.026}{.00005} \gg 1$ so the system labels this tweet as 'positive'

*all words considered,
even absent ones*

machine learning & mutual information



mutual information between F and B is defined as

$$I(F, B) \equiv \sum_{f, b} p(f, b) \log \frac{p(f, b)}{p(f)p(b)} \quad \begin{matrix} H(F) + H(B) \\ - H(F, B) \end{matrix}$$

notice first that if a feature and behavior are *independent*, $p(f, b) = p(f)p(b)$ and $I(F, B) = 0$... looks right

mutual information example

count		Sentiment
2000	I really like this course and am learning a lot	positive
800	I really hate this course and think it is a waste of time	negative
200	The course is really too simple and quite a bore	negative
3000	The course is simple , fun and <i>very</i> easy to follow	positive
1000	I'm enjoying this course a lot and learning something too	positive
400	I would enjoy myself a lot <i>if</i> I did <i>not</i> have to be in this course	negative
600	I did <i>not</i> enjoy this course enough	negative

$p(+)=.75$; $p(-)=.25$; $p(\text{hate})=800/8000$; $p(\sim\text{hate})=7200/8000$;

$p(\text{hate},+)=1/8000$; $p(\sim\text{hate},+)=6000/8000$; $p(\sim\text{hate},-)=1200/8000$; $p(\text{hate},-)=.1$;

$$I(H,S) = p(\text{hate},+) \log \frac{p(\text{hate},+)}{p(\text{hate})p(+)} + p(\sim\text{hate},+) \log \frac{p(\sim\text{hate},+)}{p(\sim\text{hate})p(+)} + p(\text{hate},-) \log \frac{p(\text{hate},-)}{p(\text{hate})p(-)} + p(\sim\text{hate},-) \log \frac{p(\sim\text{hate},-)}{p(\sim\text{hate})p(-)}$$

we get $I(\text{HATE},S) = .22$

$p(+)=.75$; $p(-)=.25$; $p(\text{course})=8000/8000$; $p(\sim\text{course})=1/8000$;

$p(\text{course},+)=.75$; $p(\sim\text{course},+)=1/8000$; $p(\sim\text{course},-)=1/8000$; $p(\text{course},-)=.25$;

we get $I(\text{COURSE},S) = .0003$

mutual information example

count		Sentiment
2000	I really like this course and am learning a lot	positive
800	I really hate this course and think it is a waste of time	negative
200	The course is really too simple and quite a bore	negative
3000	The course is simple , fun and <i>very</i> easy to follow	positive
1000	I'm enjoying myself a lot and learning something too	positive
400	I would enjoy myself a lot <i>if</i> I did <i>not</i> have to be here	negative
600	I did <i>not</i> enjoy this course enough	negative

$p(+)=.75$; $p(-)=.25$; $p(\text{hate})=800/8000$; $p(\sim\text{hate})=7200/8000$;

$p(\text{hate},+)=1/8000$; $p(\sim\text{hate},+)=6000/8000$; $p(\sim\text{hate},-)=1200/8000$; $p(\text{hate},-)=.1$;

$$I(H,S) = p(\text{hate},+) \log \frac{p(\text{hate},+)}{p(\text{hate})p(+)} + p(\sim\text{hate},+) \log \frac{p(\sim\text{hate},+)}{p(\sim\text{hate})p(+)} + p(\text{hate},-) \log \frac{p(\text{hate},-)}{p(\text{hate})p(-)} + p(\sim\text{hate},-) \log \frac{p(\sim\text{hate},-)}{p(\sim\text{hate})p(-)}$$

we get $I(\text{HATE},S) = .22$

$p(+)=.75$; $p(-)=.25$; $p(\text{course})=6600/8000$; $p(\sim\text{course})=1400/8000$;

$p(\text{course},+)=5/8$; $p(\sim\text{course},+)=1000/8000$; $p(\sim\text{course},-)=400/8000$; $p(\text{course},-)=16/80$

we get $I(\text{COURSE},S) = .001$

features: which ones, how many ...?

choosing features – use those with highest MI ...

costly to compute exhaustively

proxies – IDF; iteratively - AdaBoost, etc...

are more features always good?

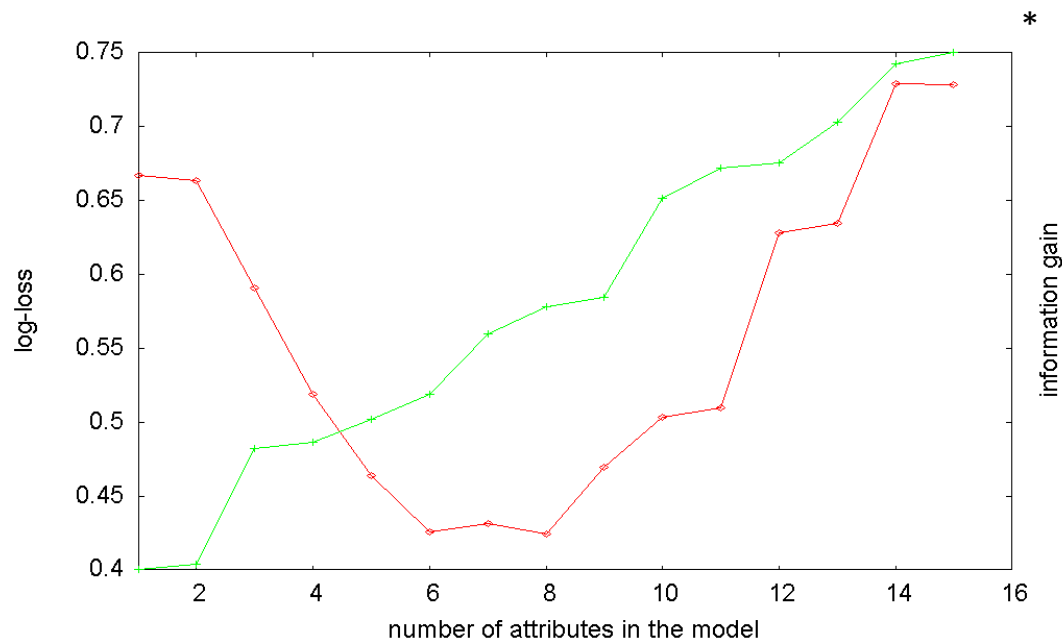
as we add features:

- NBC first improves
- then degrades! why?
- wrong features? no ..

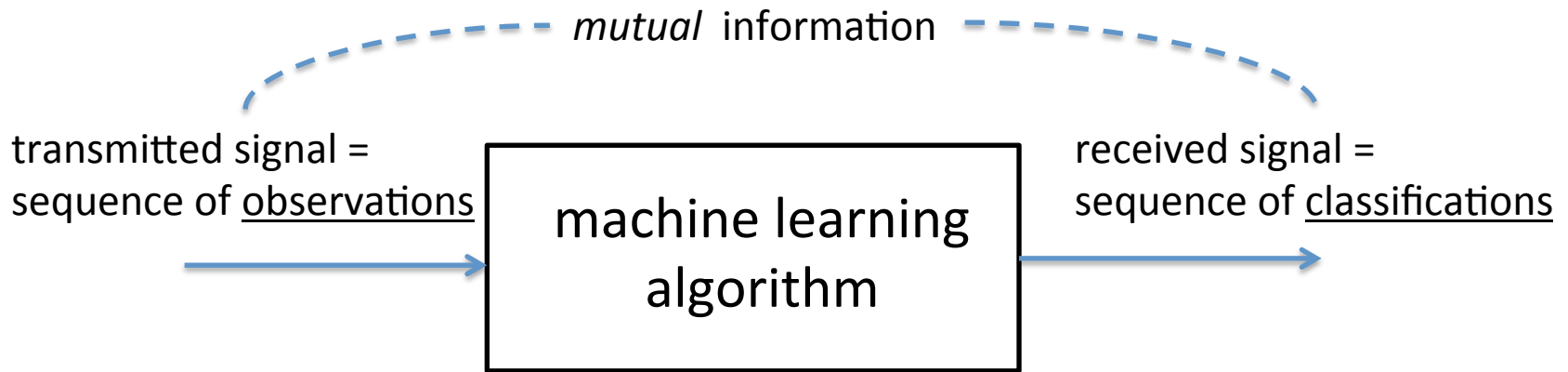
redundant features

$$I(f_i, f_j) \neq \varepsilon$$

confuses NBC that assumes
independent features!



learning and information *theory*



Shannon defined *capacity* for communications channels:

"maximum mutual information between sender and receiver per second"

what about machine learning?

*"... complexity of Bayesian learning using information theory and the VC dimension",
Haussler, Kearns and Schapire, J. Machine Learning, 1994*

`right' Bayesian classifier will eventually learn any concept

... how fast? ... it depends on the concept itself – 'VC' dimension"

opinion mining vs sentiment analysis

100s of millions of Tweets per day:

can listen to “the voice of the consumer” like never before

sentiment – brand / competitive position ... +/- counts

but: what are consumers saying / complaining about?

“book me on an American flight to New York ; I hate English food”

what does the word ‘American’ mean? nationality or airline?

“I only eat Kellogs cereals” vs. “only I eat Kellogs cereals”

what can you say about this home’s breakfast stockpile?

“took the new car on a terrible, bumpy road, it did well though”

is this family happy with their new car?

Bayesian learning using a ‘bag-of-words’ – is it enough?

➤ ‘natural language processing’ and ‘information extraction’

recap of Listen

‘mutual information’ – M.I.

statistics of language in terms of M.I.

keyword summarization using TF-IDF

communication & learning in terms of M.I.

naive Bayes classifier

limits of machine-learning

information-theoretic => feature selection

suspensions about the ‘bag of words’ approach

more importantly – *where do features come from?*

NEXT: excursion into big-data technology

using it for indexing, page-rank, TF-IDF, NBC/MI ...