#### Natural Language Processing

Lecture 05

Dirk Hovy

dirk.hovy@unibocconi.it





#### Today's Goals

- Know when (and when not) to use Regular expressions
- Understand how language/information can be modeled as probability distributions
- Understand how information can be quantified with entropy
- Learn about KL-divergence for the difference between distributions
- Understand PMI and see why it can help find collocations



#### Flexible Matches: Regular Expressions

#### The promise...

WHENEVER I LEARN A
NEW SKILL I CONCOCT
ELABORATE FANTASY
SCENARIOS WHERE IT
LETS ME SAVE THE DAY.

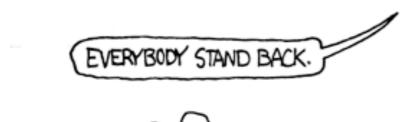
OH NO! THE KILLER MUST HAVE POLLOWED HER ON VACATION!



BUT TO FIND THEM WE'D HAVE TO SEARCH THROUGH 200 MB OF EMAILS LOOKING FOR SOMETHING FORMATTED LIKE AN ADDRESS!



IT'S HOPELESS!



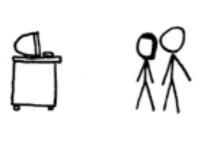
















#### Is it an (Email) Address?

- notMyFault@webmail.com
- smithie123@gmx
- Free stuff@unibocconi.it
- mark\_my\_words@hotmail;com
- truthOrDare@webmail.in
- look@me@twitter.com
- how2GetAnts@aol.dfdsfgfdsgfd

NAME

@

DOMAIN

. CODE



#### Simple Matching

sequence	Matches				
e	any single occurrence of e				
at	<pre>at, rat, mat, sat, cat, attack,   attention, later</pre>				

#### Quantifiers

	Means	Example	Matches
*	0 or more	cooo*l	cool, coool
+	1 or more	hello+	hello, helloo, hellooooooo
?	0 or 1	fr?og	fog, frog

#### Special Characters

	Means	Example	Matches		
	any single character	.el	eel, Nel, gel		
\n	newline character (line break)	\n+	One or more line breaks		
\t	a tab stop	\t+	One or more tabs		
\d	a single digit [0-9]	B\d	во, в1,, в9		
\D	a non-digit	\D.t	' t, But, eat		
\w	any alphanumberic character	\w\w\w	Top, WOO, ash, bee,		
\W	non-alphanumberic character				
\s	a whitespace character				
\\$	a non-whitespace character				
\	"Escapes" special characters to match them	.+ \.com	abc.com, united.com		
٨	the beginning of the input string	^ • • •	First word in line		
<b>\$</b>	the end of the input string	^\n\$	Empty line		

#### Classes

	Means	Example	Matches			
[abc]	Match any of a, b, c	[bcrms]at	bat, cat, rat, mat, sat			
[^abc]	Match anything BUT a, b, c	te[^ ]+s	tens, tests, teens, texts, terrors			
[a-z]	Match any lowercase character	[a-z][a-z]t	act, ant, not, wit			
[A-Z]	Match any uppercase character	[A-Z]	Ahab, Brit, In a,, York			
[0-9]	Match any digit	DIN A[0-9]	DIN A0, DIN A1,, DIN A9			



#### Groups

	Means	Example	Matches		
(abc)	Match abc	.(ar).	hard, cart, fare,		
(ab c)	Match ab OR c	(ab c)ate	abate, cate		

#### Matching Addresses

NAME @ DOMAIN . CODE

```
^[A-Za-z0-9_\.-]+@[A-Za-z0-9_\.-]+\.[A-Za-z0-9_][A-Za-z0-9_]+$
```



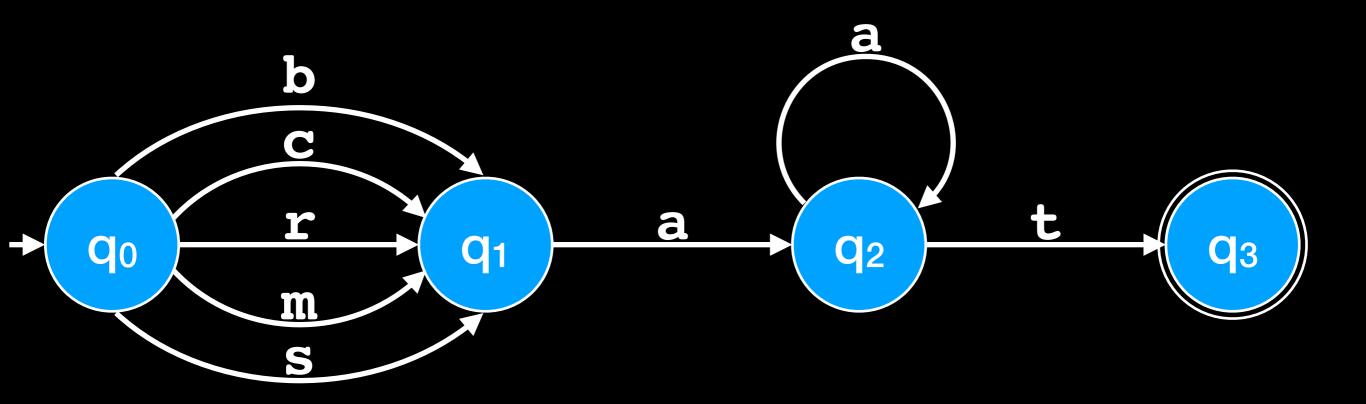
http://xkcd.com/1171/

A (W w) ord of [Ww] arning

(?:(?:\r\n)?[\t])\*(?:\?:(?:[^()<>\oldonountering, \t])\*(?:(?:\r\n)?[\t])\*(?:\r\n)?[\t]



#### RegEx as Automata



[bcrms]a+t



## The Probability of Words

#### Probability of a Word

"It must be recognized that the notion 'probability of a sentence' is an entirely useless one, under any known interpretation of this term."

—Noam Chomsky (grumpy linguist)

Choose a word w
Open a page at random and point at a word:
Is it w?

HOW OFTEN WE

HAVE SEEN W

$$C(w)$$

$$P(w) = \frac{c(v)}{\sum c(v)}$$
...ALL WORDS

#### Conditional Probability

We finish each others'

SENTENCES

SANDWICHES

MONES

WHATS MORE LIKELY?



#### Conditional Probabilities

\*TOTALLY MADE UP NUMBERS

h	W	P(w h)*		
	milk	0,42		
tea with	sugar	0,35		
lea Willi	a	0,18		
	stevia	0,05		
	win	0,25		
for the	majority	0,21		
for the	birds	0,15		
7				

PSUM TO 1.0

Bocconi

## Where Probabilities Come From WE NEED A WAY TO ASSIGN

P(WORD I "WE FINISH EACH OTHERS")

We finish each others' ...

HOW OFTEN WE

HAVE SEEN W C(w)  $P(w|h) = \sum_{h \in V} c(h, w)$ 

... AFTER THE OTHER WORDS



#### Count in 57m Tweets

MAXIMUM LIKELIHOOD ESTIMATION

```
12 The weather today is just
 9 The weather today is so
9 the weather today is slightly
 8 The weather today is perfect
 5 The weather today is beautiful
4 The weather today is slightly
 3 the weather today is so
 3 the weather today is perfect
 3 The weather today is nearly
 3 the weather today is bitter
 3 The weather today is absolutely
 2 The weather today is wonderful
 2 The weather today is beyond
 2 The weather today is amazing
 2 The weather today is a
 1 the weather today is worth
 1 the weather today is weird
1 The weather today is too
 1 the weather today is the
 1 The weather today is that
 1 the weather today is that
 1 The weather today is splendid
 1 THE WEATHER TODAY IS SO
 1 the weather today is simply
 1 The weather today is sickening
 1 The weather today is seriously
 1 The weather today is pretty
 1 the weather today is pretty
 1 The weather today is Perrfff
 1 the weather today is PERFECT
```

(MLE)

#### Probability Distributions

mathematical way to describe a sample

def p(number\_on\_die): 
$$P(x;N) = \frac{1}{N}$$
 return 0.1667

discrete or continuous

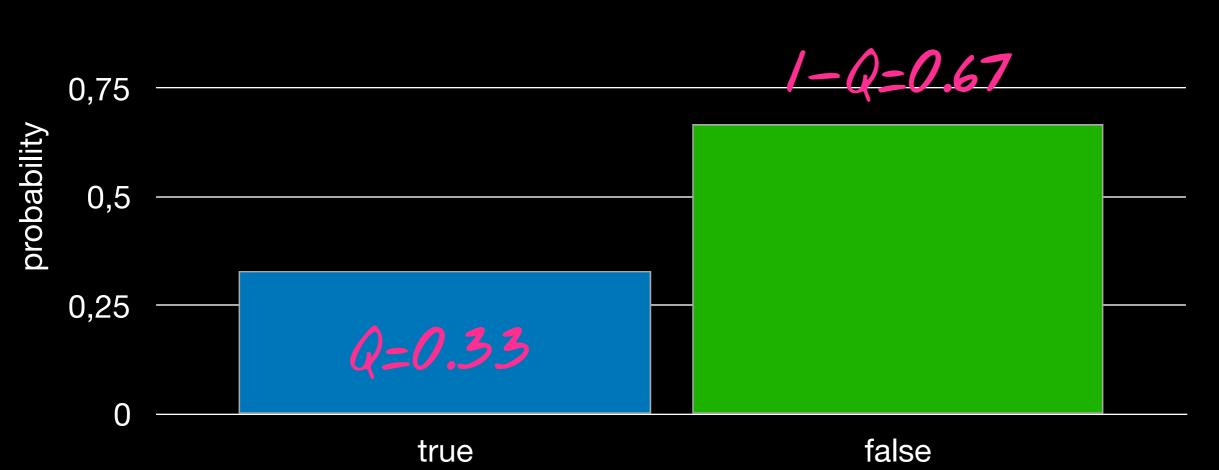


- define "shape" and properties with parameters
- compute probability for any x

#### Bernoulli Distribution



Function: 
$$P(x;q) = \left\{ \begin{array}{ll} 1-q & \text{if } x=0 \\ q & \text{if } x=1 \end{array} \right. \text{SUMS} \quad \begin{array}{ll} \text{Bernoulli} \\ \text{I.0} \end{array}$$



Bocconi

Jacob

#### Bernoulli Distribution

- has only two outcomes
- the probability of failure is the complement of success
- Examples: binary classification, indicator features



#### **L.** Categorical Distribution

VECTOR WITH ALL PROBABILITIES Parameters:  $\theta$  SUMS TO 1.0 SE VALUE AT Function:  $P(x;\theta) = \prod_{j} \theta_{j}^{\mathbb{I}(x_{j}=1)}$  VECTOR POSITION FOR  $\Theta = \begin{bmatrix} 0.16 & 0.3 & 0.1 & 0.37 & 0.07 \end{bmatrix}$ "PARTY 2" = [ 0 1 0 0 ] Milipedord

PARTY 2") = 1 \* 0.3 \* 1 \* 1 \* 1 0,25



#### LCategorical Distribution

- has many outcomes (also called multinomial)
- if outcomes are numeric, we can compute the expected average value, or expectation

$$\mathbb{E}(\mathbf{X}) = \sum_{i=1}^{N} x_i \cdot P(x_i)$$

E(die\_roll) = 
$$\mathbf{1} \cdot 0.1667 + \mathbf{2} \cdot 0.1667 + \mathbf{3} \cdot 0.1667 + \mathbf{4} \cdot 0.1667 + \mathbf{5} \cdot 0.1667 + \mathbf{6} \cdot 0.1667 + \mathbf{5} \cdot 0.1667 + \mathbf{5} \cdot 0.1667 + \mathbf{6} \cdot 0.1667$$

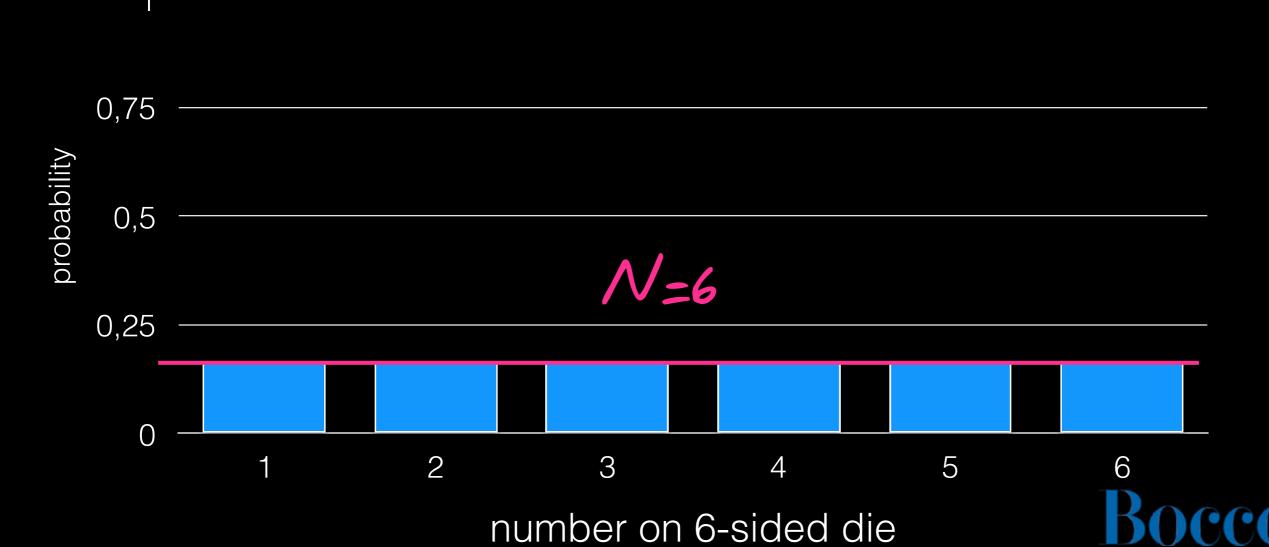
Examples: word sequences, topics, multi-class labels, etc.



#### Uniform Distribution

Parameters: N NUMBER OF EVENTS

Function: 
$$P(x; N) = \frac{1}{N} SVMS 70 1.0$$



#### Uniform Distribution

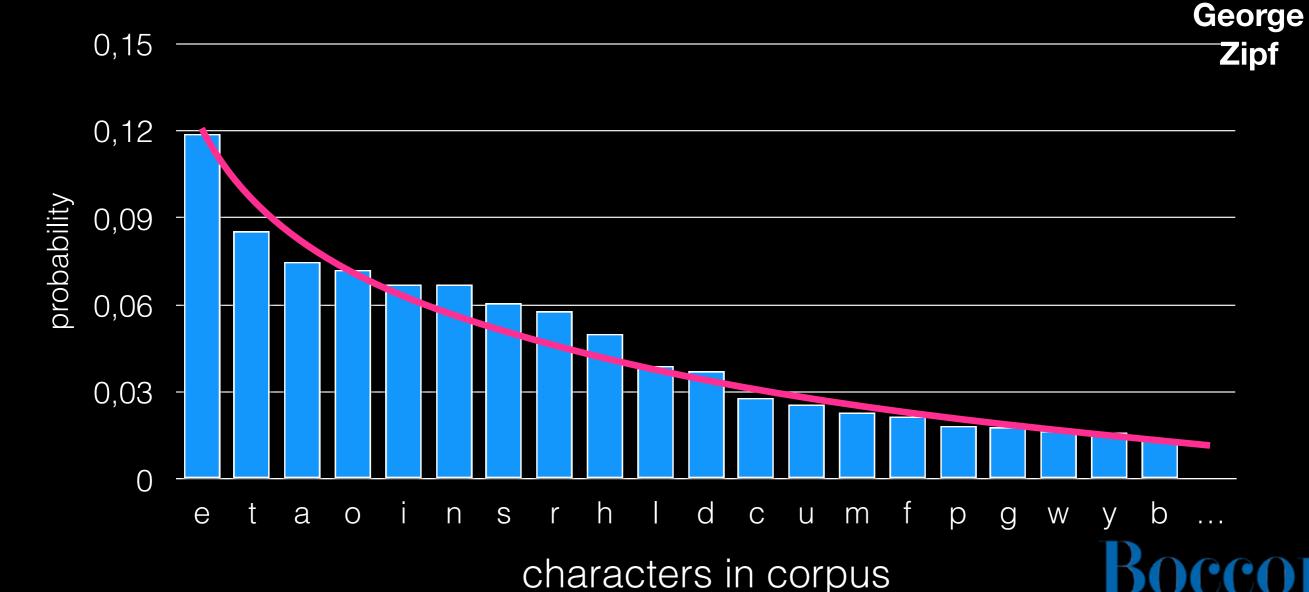
- special case of discrete distros (Bernoulli, categorical)
- all outcomes are equally likely, so it's hardest to predict
- Examples: fair coin toss, die roll



#### Power-Law Distribution

Parameters: k STEEPNESS OF CURVE

Function:  $P(x;k) = kx^{-(k+1)}$ 



#### Power-Law Distribution

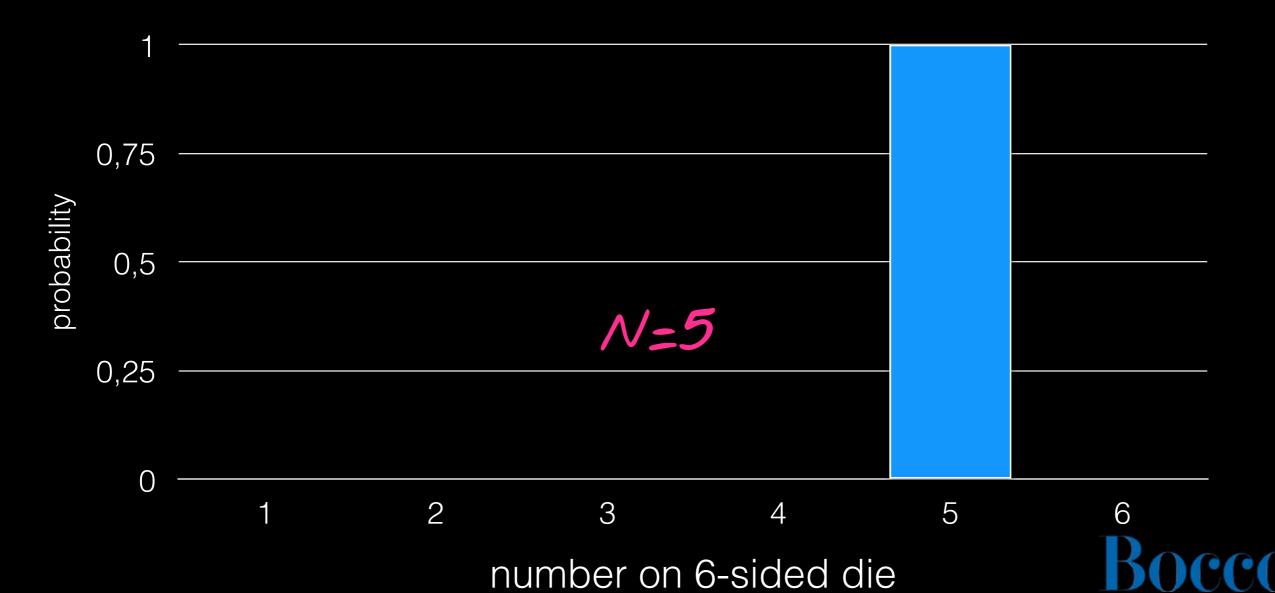
- has many outcomes
- most frequent outcome is k times more likely than second most frequent, which is k times more likely than third most frequent, etc.
- top N outcomes account for majority of observations
- easy to predict outcome of a random draw
- has a "long tail" of rare outcomes
- mean and median are very different!
- Examples: frequency of words, sounds, or letters in a language, city sizes, wealth distribution. "rich get richer" effect



#### One-Hot Distribution

Parameters: n ONLY TRUE EVENT

Function: P(x; n) = 1 if x=n; else 0



#### **One-Hot Distribution**

- special case of discrete distros (Bernoulli, categorical)
- easy way to represent a single truth (neural networks)
- Examples: correct answer in multi-class problems

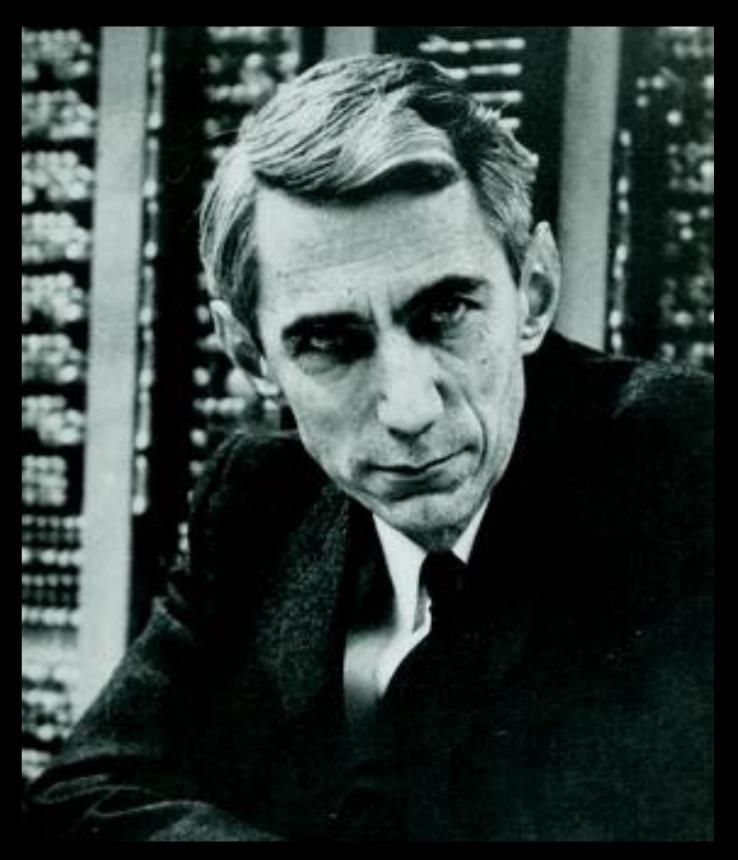


# How Skewed are We? Entropy

#### Claude Shannon

#### 1916-2001

- His master's thesis founded a new field: digital circuits
- Invented entropy to quantify language – and a flamethrowing trumpet
- Enabled NLP, cryptography, modern computers...
- Died of Alzheimer's, oblivious to his own inventions' impact





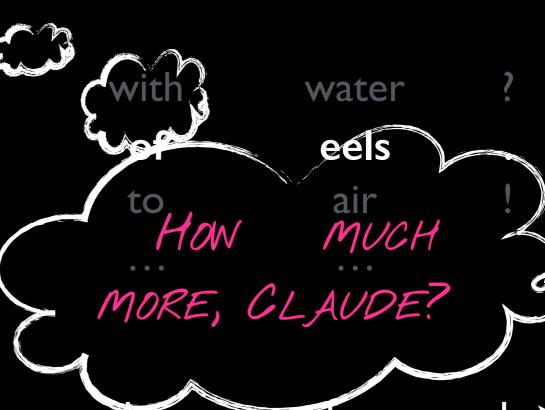
#### Shannon Game



WHAT'S THE NEXT WORD?









entropy

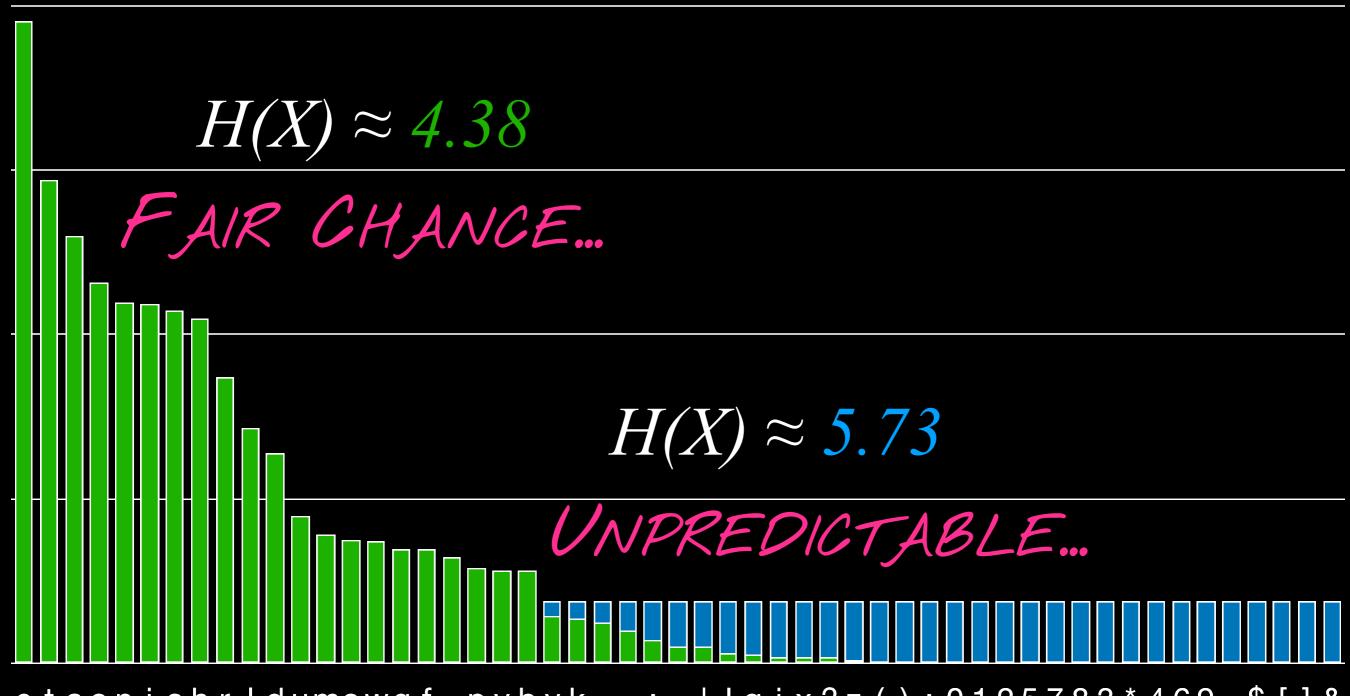
$$H(X) = -\sum_{x} p(x) \log p(x)$$

**Information** 

p(x)

#### Entropy in Use

WHATS THE NEXT LETTER?



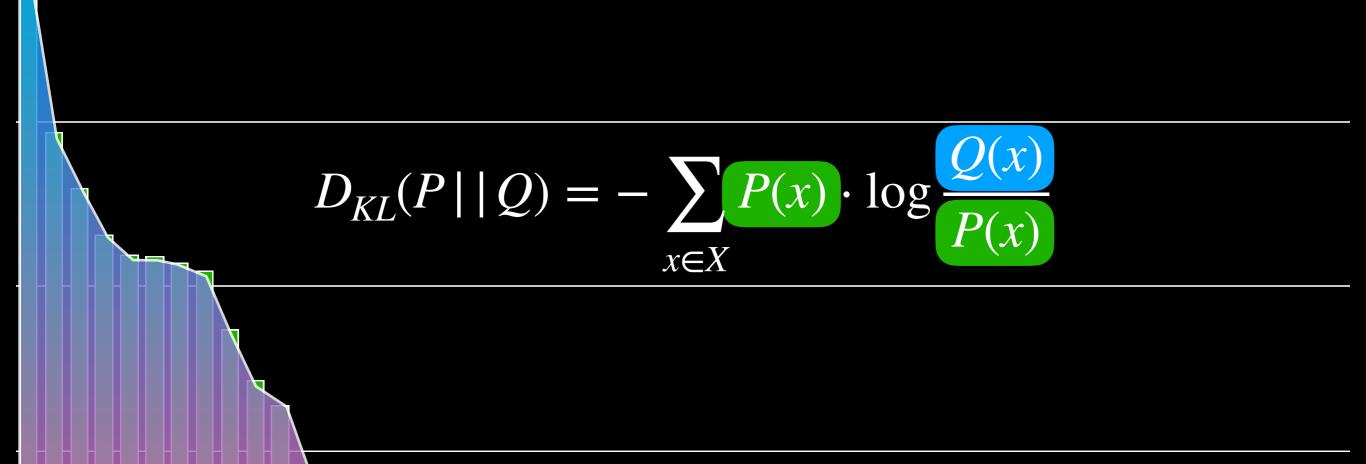
etaonishrldumcwgf,pybvk,-; '!qjx?z():0125783\*469\_\$[]&...35

#### What's the Difference: Kullback-Leibler Divergence



#### Entropy in Use

"RELATIVE ENTROPY"

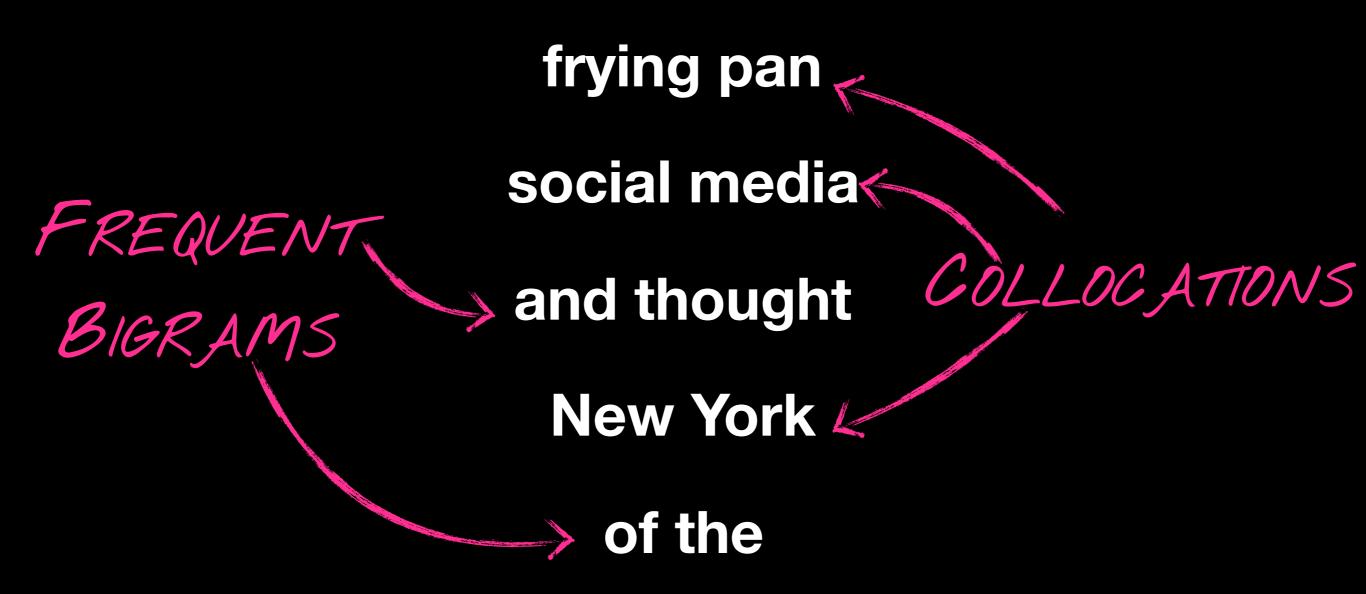


etaonishrldumcwgf,pybvk,-; '!qjx?z():0125783\*469\_\$[]&

# Frequent Company: Pointwise Mutual Information



#### Some are not like the Others



#### Mutual Informativity

HOW WELL CAN WE GUESS THE BLANK?

social \_\_\_\_

and

media

the

## Pointwise Mutual Information CHANCE OF SEEING THEM TOGETHER

 $PMI(x, y) = log \underbrace{P(x, y)}_{P(x)P(y)}$   $\underbrace{P(x)P(y)}_{SEEING}$ 

X	У	c(x)	c(y)	c(xy)	P(x)	P(y)	P(x, y)	PMI(x; y)
moby	dick	83	83	82	0.0003	0.0003	0.0003	3.48
captain	ahab	327	511	61	0.0013	0.0020	0.0002	1.97
white	whale	280	1150	106	0.0011	0.0045	0.0004	1.93
under	the	119	14175	45	0.0005	0.0553	0.0002	0.83
is	а	1690	4636	110	0.0066	0.0181	0.0004	0.56

c(X) = 256,149c(XY) = 256,148

Bocconi

#### Wrapping up

#### Take home points

- Regular expressions allow us to search for flexible patterns
- Word sequences can be seen as discrete probability distributions
- Entropy allows us to quantify how surprising/predictable an outcome is
- KL-divergence tells us how different two distributions are
- PMI tells us how likely one word is to occur with/without another to find collocations

