Data-Intensive Distributed Computing

CS 431/631 451/651 (Fall 2019)

Part 3: Analyzing Text (1/2)

September 26, 2019

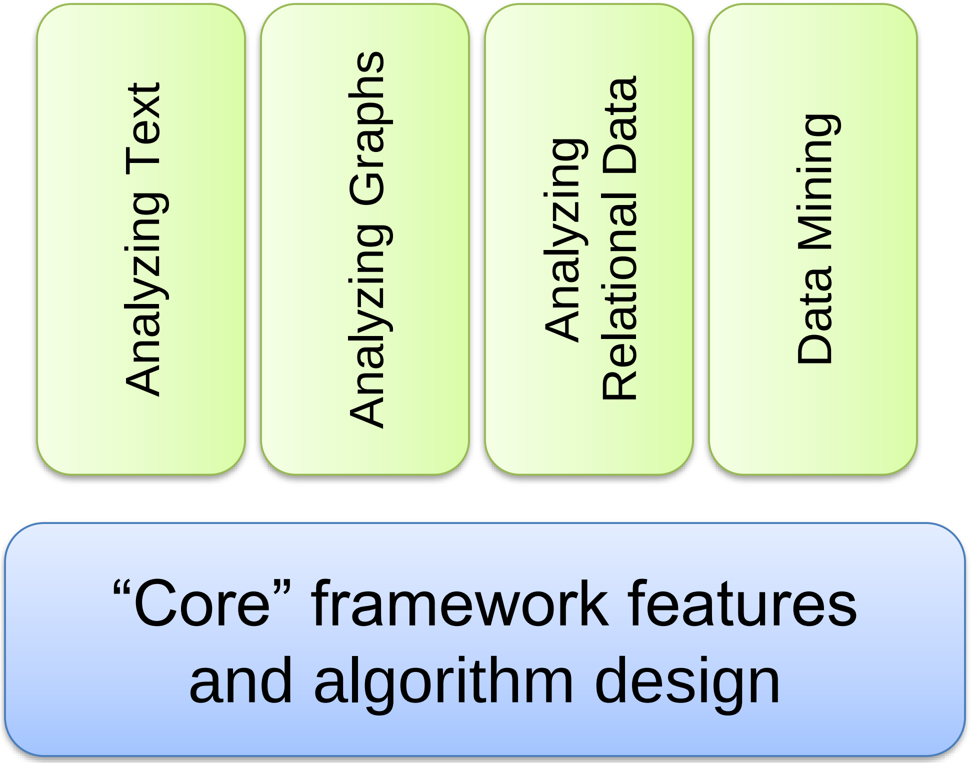
Ali Abedi

These slides are available at https://www.student.cs.uwaterloo.ca/~cs451

Structure of the Course

"Core" framework features and algorithm design

Structure of the Course



Analyzing Text

Analyzing Graphs

Analyzing Relational Data

Data Mining

“Core” framework features and algorithm design

Count.

Source: http://www.flickr.com/photos/guvnah/7861418602/

Count

(Efficiently)

```
class Mapper {
  def map(key: Long, value: String) = {
    for (word <- tokenize(value)) {
      emit(word, 1)
    }
  }
}

class Reducer {
  def reduce(key: String, values: Iterable[Int]) = {
    for (value <- values) {
      sum += value
    }
    emit(key, sum)
  }
}
```

Pairs. Stripes.

Seems pretty trivial…

More than a “toy problem”?
Answer: language models

Language Models

$P(w_1, w_2, \ldots, w_T)$ Assigning a probability to a sentence

Why?

- **Machine translation**
  - P(High winds tonight) > P(Large winds tonight)
- **Spell Correction**
  - P(Waterloo is a great city) > P(Waterloo is a grate city)
- **Speech recognition**
  - P (I saw a van) > P(eyes awe of an)

Slide: from Dan Jurafsky

Language Models

$$P(w_1, w_2, \ldots, w_T)$$

$$= P(w_1)P(w_2|w_1)P(w_3|w_1, w_2)\ldots P(w_T|w_1, \ldots, w_{T-1})$$

[chain rule]

P("Waterloo is a great city") =
P(Waterloo) x P(is | Waterloo) x P(a | Waterloo is)
x P(great | Waterloo is a)
x P(city | Waterloo is a great)

Is this tractable?

Approximating Probabilities: *N*-Grams

Basic idea: limit history to fixed number of (*N* – 1) words (Markov Assumption)

$$P(w_k|w_1,\ldots,w_{k-1}) \approx P(w_k|w_{k-N+1},\ldots,w_{k-1})$$

N=1: Unigram Language Model

$$P(w_k|w_1,\ldots,w_{k-1}) \approx P(w_k)$$

$$\Rightarrow P(w_1,w_2,\ldots,w_T) \approx P(w_1)P(w_2)\ldots P(w_T)$$

Approximating Probabilities: *N*-Grams

Basic idea: limit history to fixed number of (*N* – 1) words (Markov Assumption)

$$P(w_k|w_1,\ldots,w_{k-1}) \approx P(w_k|w_{k-N+1},\ldots,w_{k-1})$$

N=2: Bigram Language Model

$$P(w_k|w_1,\ldots,w_{k-1}) \approx P(w_k|w_{k-1})$$

$$\Rightarrow P(w_1,w_2,\ldots,w_T) \approx P(w_1|<\mathrm{S}>)P(w_2|w_1)\ldots P(w_T|w_{T-1})$$

Approximating Probabilities: *N*-Grams

Basic idea: limit history to fixed number of (*N* – 1) words
(Markov Assumption)

$$P(w_k|w_1,\ldots,w_{k-1}) \approx P(w_k|w_{k-N+1},\ldots,w_{k-1})$$

N=3: Trigram Language Model

$$P(w_k|w_1,\ldots,w_{k-1}) \approx P(w_k|w_{k-2},w_{k-1})$$

$$\Rightarrow P(w_1,w_2,\ldots,w_T) \approx P(w_1|< \mathrm{S} >< \mathrm{S} >)\ldots P(w_T|w_{T-2}w_{T-1})$$

Building *N*-Gram Language Models

Compute maximum likelihood estimates (MLE) for Individual *n*-gram probabilities

Unigram $$P(w_i) = \frac{C(w_i)}{N}$$

Fancy way of saying: count + divide

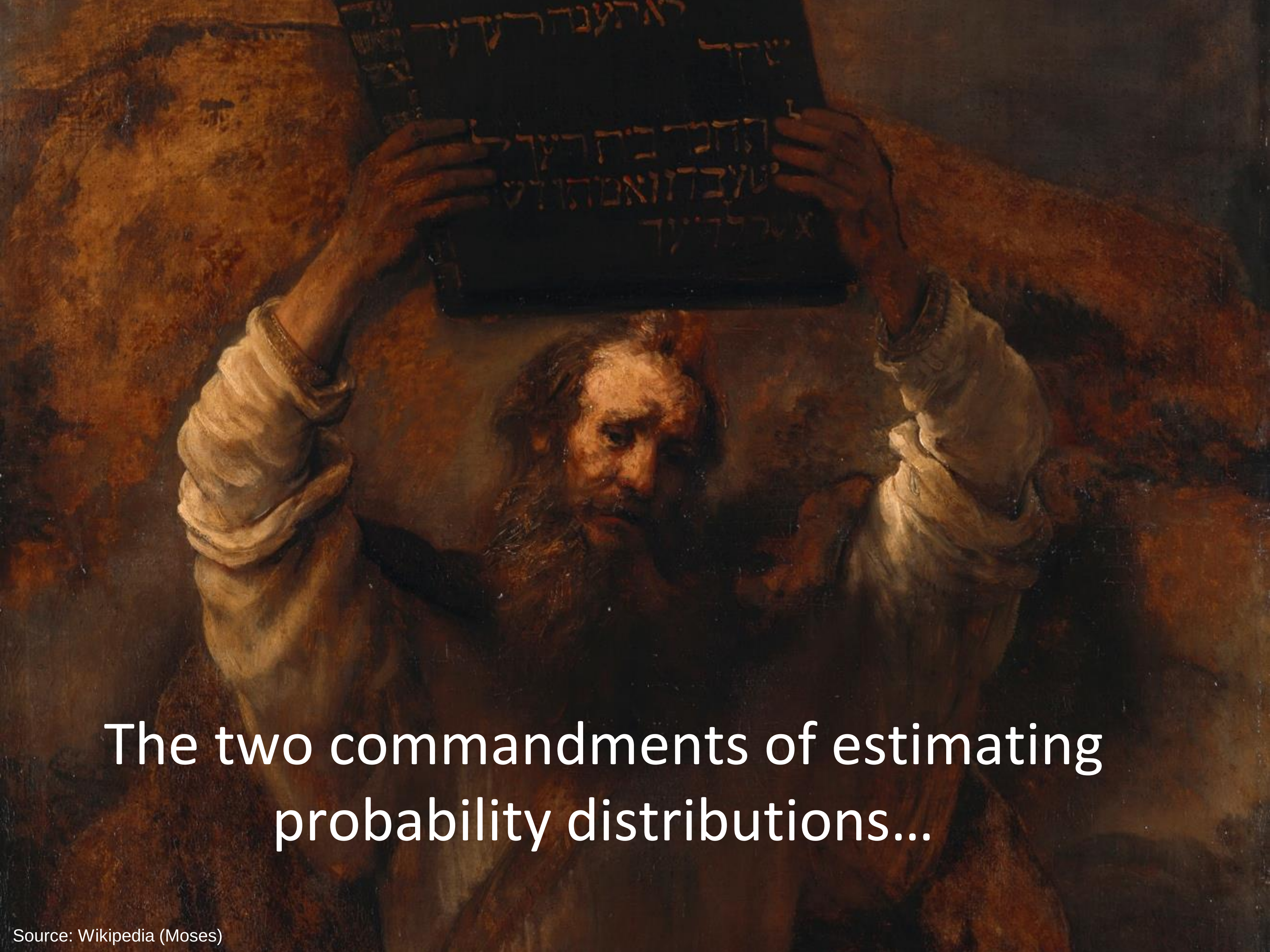
Bigram $$P(w_i, w_j) = \frac{C(w_i, w_j)}{N}$$

$$P(w_j|w_i) = \frac{P(w_i, w_j)}{P(w_i)} = \frac{C(w_i, w_j)}{\sum_w C(w_i, w)} \overset{?}{=} \frac{C(w_i, w_j)}{C(w_i)}$$

Minor detail here…

Generalizes to higher-order n-grams
State of the art models use ~5-grams

We already know how to do this in MapReduce!

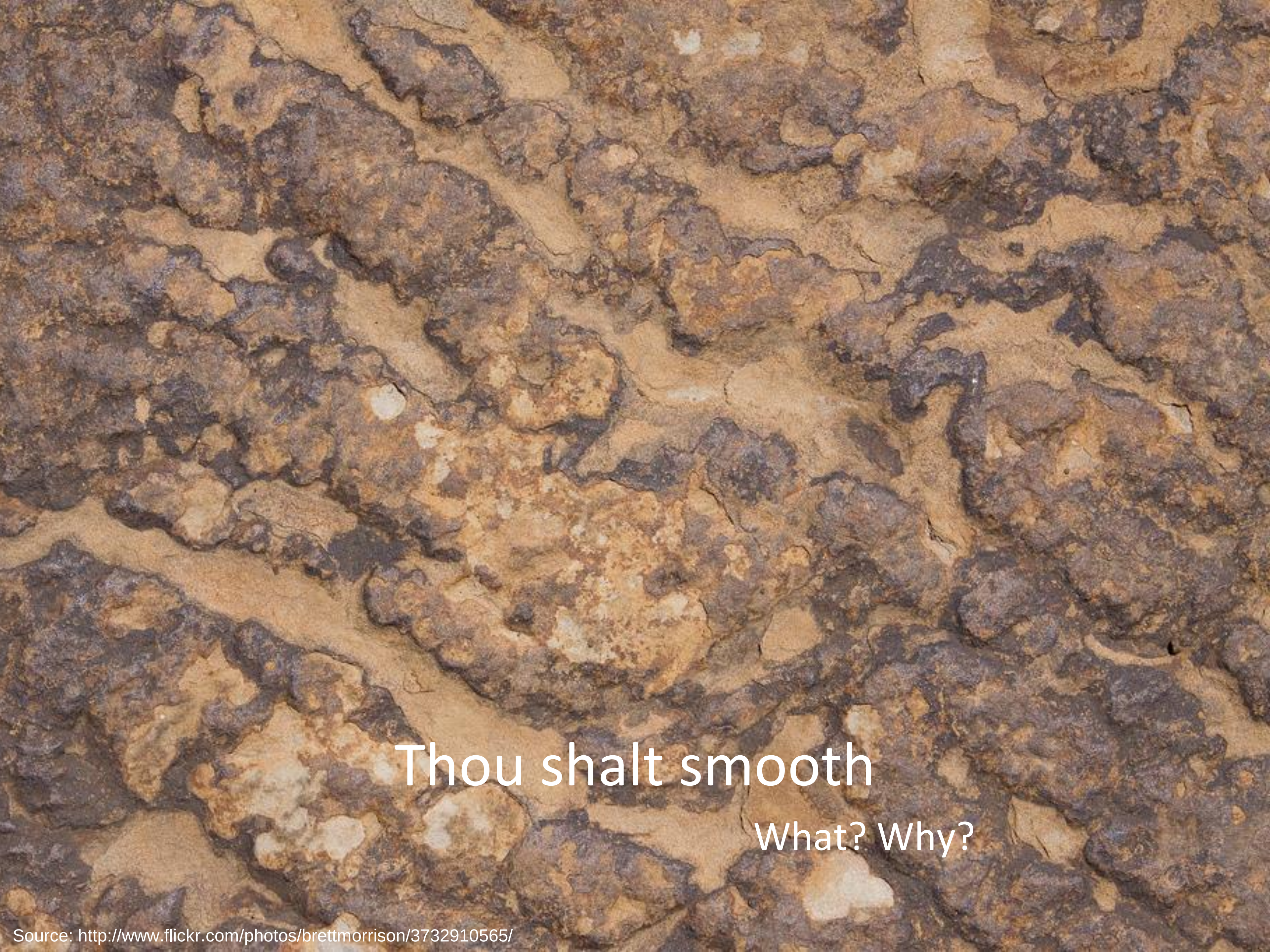


The two commandments of estimating probability distributions…

Source: Wikipedia (Moses)

Probabilities must sum up to one

Source: http://www.flickr.com/photos/37680518@N03/7746322384/



Thou shalt smooth

What? Why?

Source: http://www.flickr.com/photos/brettmorrison/3732910565/

Example: Bigram Language Model

<s> I am Sam </s>
<s> Sam I am </s>
<s> I do not like green eggs and ham </s>

Training Corpus

P(I | <s>) = 2/3 = 0.67
P(am | I) = 2/3 = 0.67
P(</s> | Sam)= 1/2 = 0.50
...

P(Sam | <s>) = 1/3 = 0.33
P(do | I) = 1/3 = 0.33
P(Sam | am) = 1/2 = 0.50

Bigram Probability Estimates

Note: We don’t ever cross sentence boundaries

Data Sparsity

P(I | <s>) = 2/3 = 0.67

P(am | I) = 2/3 = 0.67

P(</s> | Sam)= 1/2 = 0.50

...

P(Sam | <s>) = 1/3 = 0.33

P(do | I) = 1/3 = 0.33

P(Sam | am) = 1/2 = 0.50

Bigram Probability Estimates

P(I like ham)

= P(I | <s>) P(like | I) P(ham | like) P(</s> | ham)

= 0

Why is this bad?

Issue: Sparsity!

Thou shalt smooth!

Zeros are bad for any statistical estimator

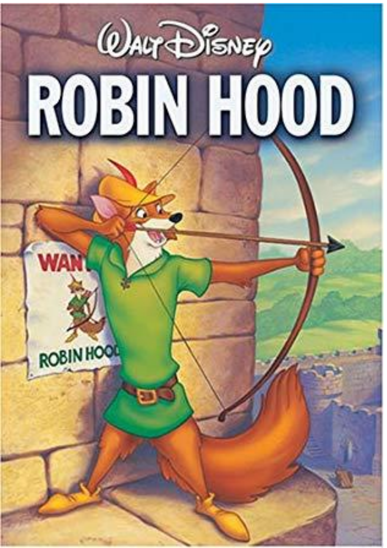
Need better estimators because MLEs give us a lot of zeros

A distribution without zeros is “smoother”

The Robin Hood Philosophy: Take from the rich (seen *n*-grams) and give to the poor (unseen *n*-grams)

Need better estimators because MLEs give us a lot of zeros

A distribution without zeros is “smoother”



Lots of techniques:

Laplace, Good-Turing, Katz backoff, Jelinek-Mercer

Kneser-Ney represents best practice

Laplace Smoothing

Learn fancy words for simple ideas!

Simplest and oldest smoothing technique

Just add 1 to all *n*-gram counts including the unseen ones

So, what do the revised estimates look like?

Laplace Smoothing

Unigrams

$$P_{MLE}(w_i) = \frac{C(w_i)}{N} \longrightarrow P_{LAP}(w_i) = \frac{C(w_i) + 1}{N + V}$$

Bigrams

$$P_{MLE}(w_i, w_j) = \frac{C(w_i, w_j)}{N} \longrightarrow P_{LAP}(w_i, w_j) = \frac{C(w_i, w_j) + 1}{N + V^2}$$

What if we don't know *V*?

Jelinek-Mercer Smoothing: Interpolation

Mix higher-order with lower-order models to defeat sparsity

Mix = Weighted Linear Combination

$$P(w_k|w_{k-2}w_{k-1}) =$$

$$\lambda_1 P(w_k|w_{k-2}w_{k-1}) + \lambda_2 P(w_k|w_{k-1}) + \lambda_3 P(w_k)$$

$$0 <= \lambda_i <= 1 \qquad \sum_i \lambda_i = 1$$

Kneser-Ney Smoothing

Interpolate discounted model with a special "continuation" *n*-gram model

Based on appearance of *n*-grams in different contexts

Excellent performance, state of the art

$$P_{KN}(w_k|w_{k-1}) = \frac{C(w_{k-1}w_k) - D}{C(w_{k-1})} + \beta(w_k)P_{CONT}(w_k)$$

$$P_{CONT}(w_i) = \frac{N(\bullet\ w_i)}{\sum_{w'} N(\bullet\ w')}$$

$N(\bullet\ w_i)$ = number of different contexts w_i has appeared in

Kneser-Ney Smoothing: Intuition

I can’t see without my ___________

“San Francisco” occurs a lot

I can’t see without my Francisco?

Stupid Backoff

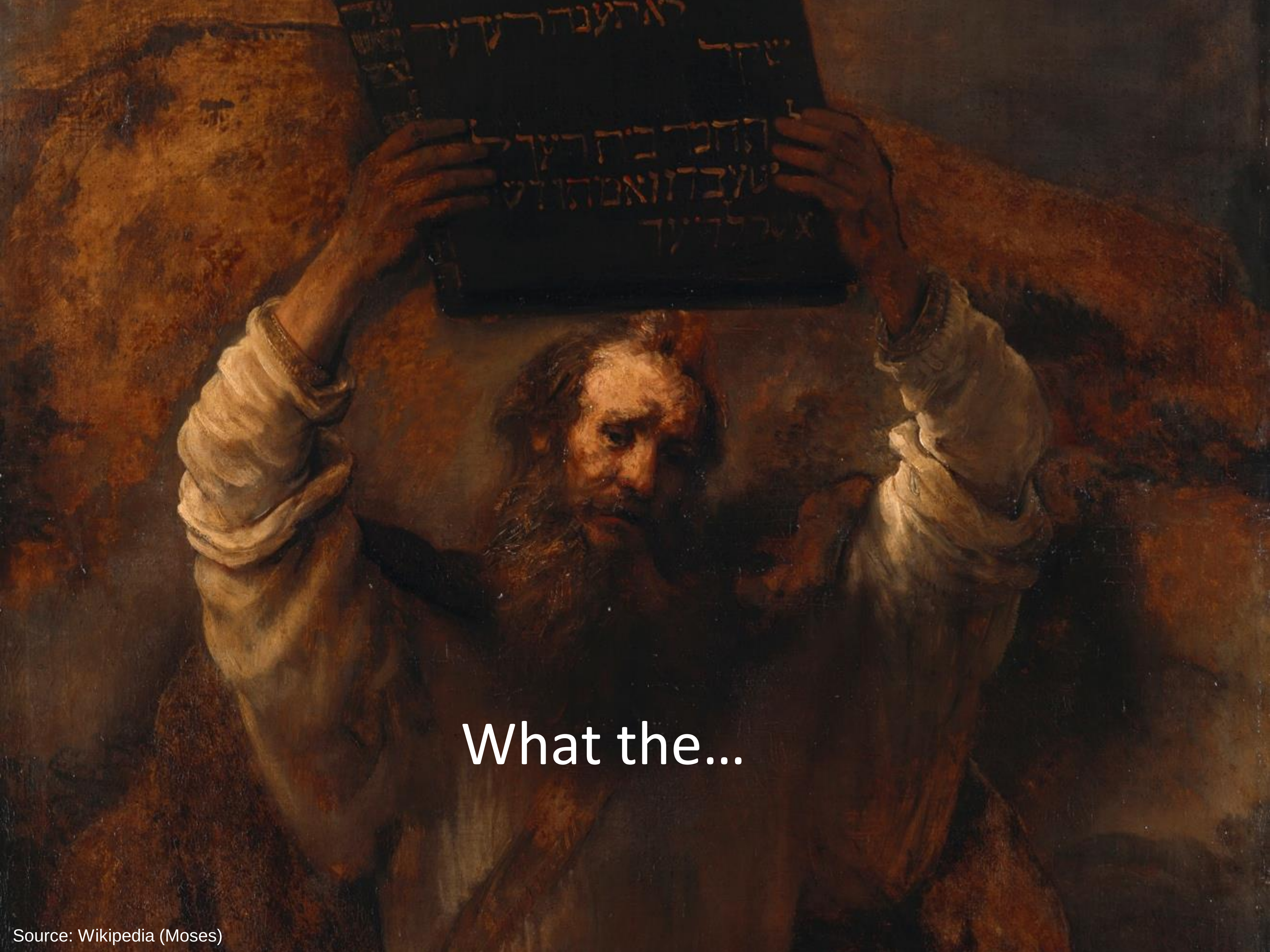
Let's break all the rules:

$$S(w_i|w_{i-k+1}^{i-1}) = \begin{cases} \frac{f(w_{i-k+1}^{i})}{f(w_{i-k+1}^{i-1})} & \text{if } f(w_{i-k+1}^{i}) > 0 \\ \alpha S(w_i|w_{i-k+2}^{i-1}) & \text{otherwise} \end{cases}$$

$$S(w_i) = \frac{f(w_i)}{N}$$

But throw *lots* of data at the problem!

Source: Brants et al. (EMNLP 2007)



What the…

Source: Wikipedia (Moses)

Stupid Backoff Implementation: Pairs!

Straightforward approach: count each order separately

A B ← remember this value

A B C $S(C|A\ B) = f(A\ B\ C)/f(A\ B)$

A B D $S(D|A\ B) = f(A\ B\ D)/f(A\ B)$

A B E $S(E|A\ B) = f(A\ B\ E)/f(A\ B)$

… …

More clever approach: count all orders together

A B ← remember this value

A B C ← remember this value

A B C P

A B C Q

A B D ← remember this value

A B D X

A B D Y

…

Stupid Backoff: Additional Optimizations

Replace strings with integers

Assign ids based on frequency (better compression using vbyte)

Partition by bigram for better load balancing

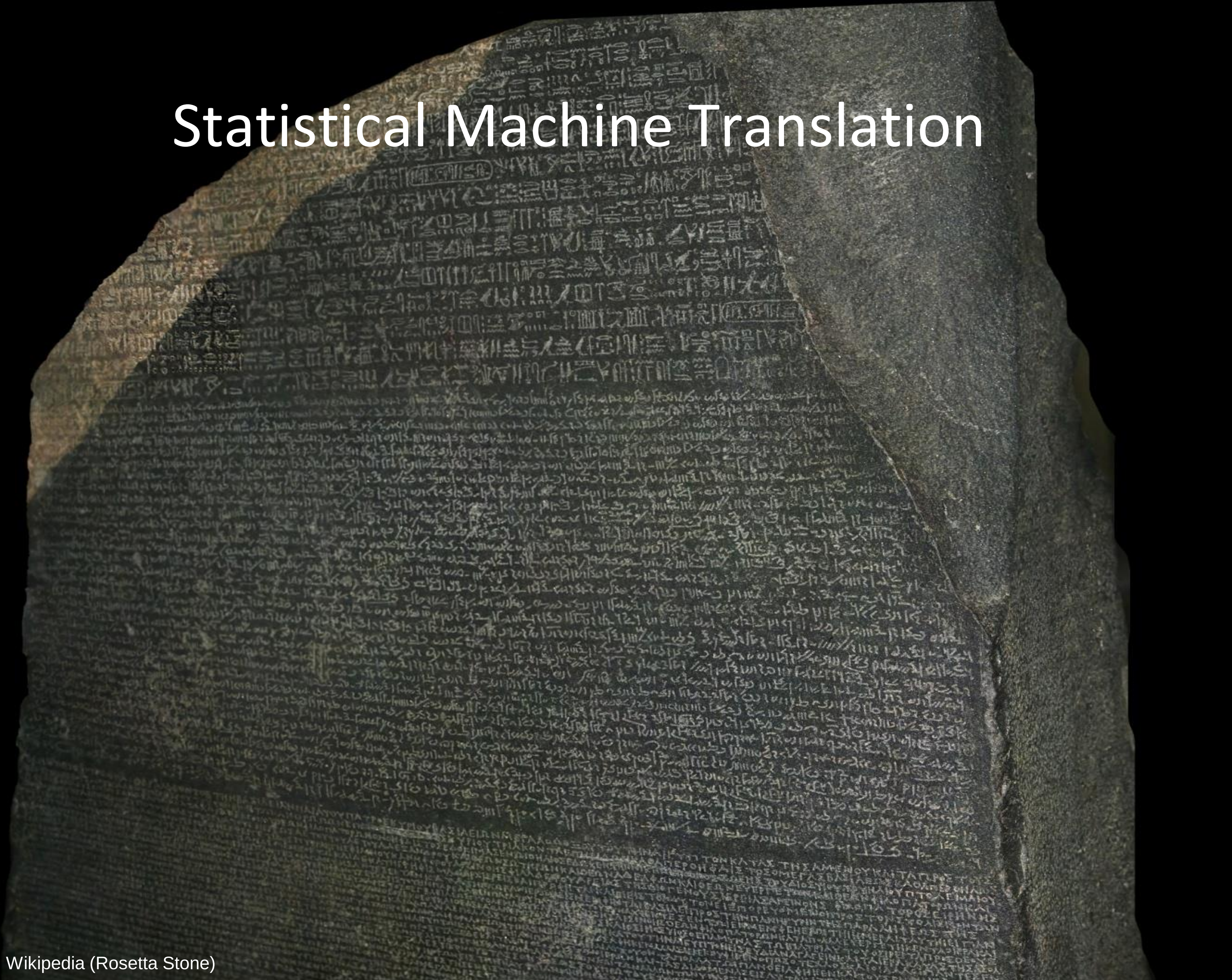
Replicate all unigram counts

State of the art smoothing (less data)

vs. Count and divide (more data)

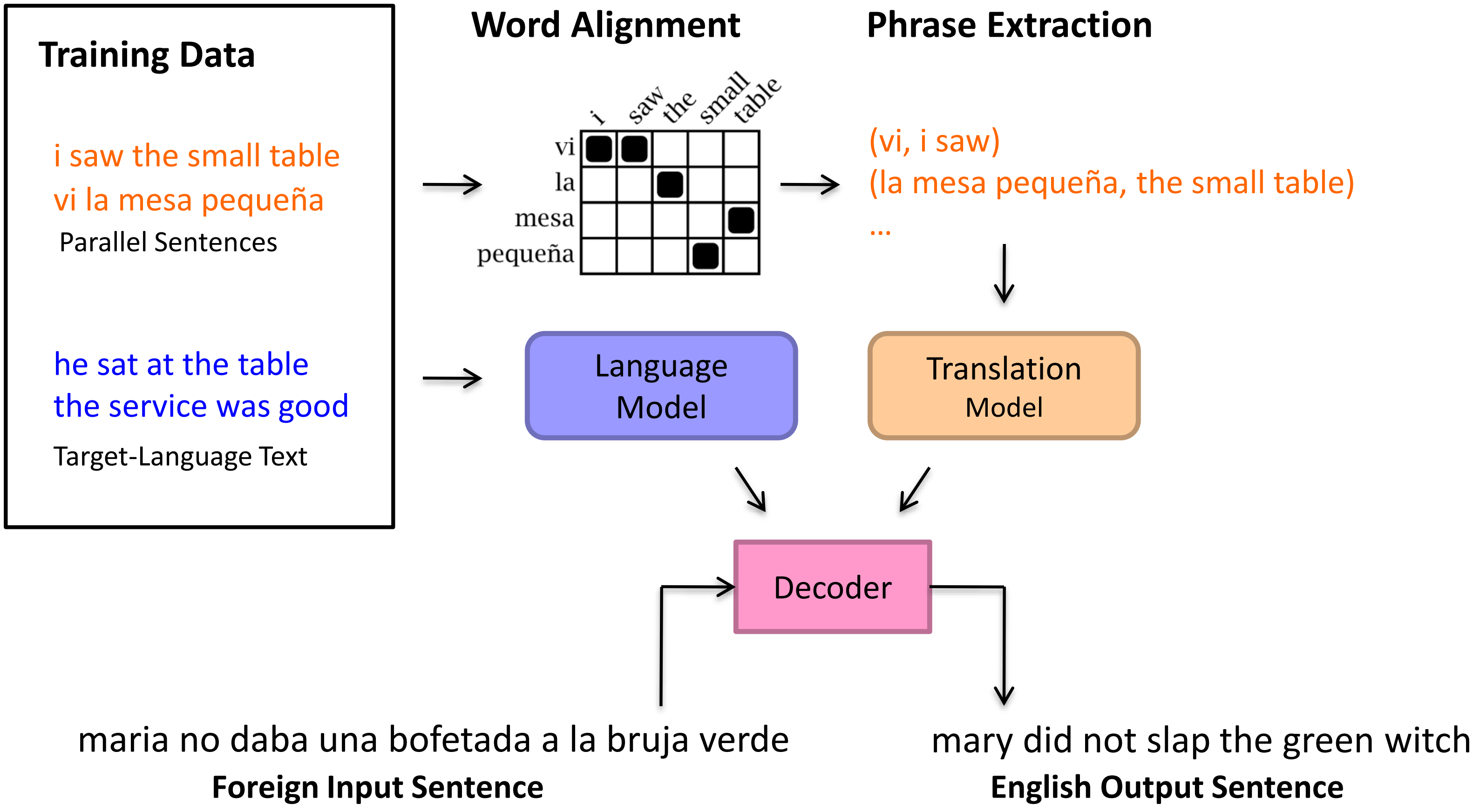
Source: Wikipedia (Boxing)

Statistical Machine Translation



Source: Wikipedia (Rosetta Stone)

Statistical Machine Translation



Training Data

i saw the small table
vi la mesa pequeña
Parallel Sentences

he sat at the table
the service was good
Target-Language Text

Word Alignment

	i	saw	the	small	table
vi	■	■			
la			■		
mesa					■
pequeña				■	

Phrase Extraction

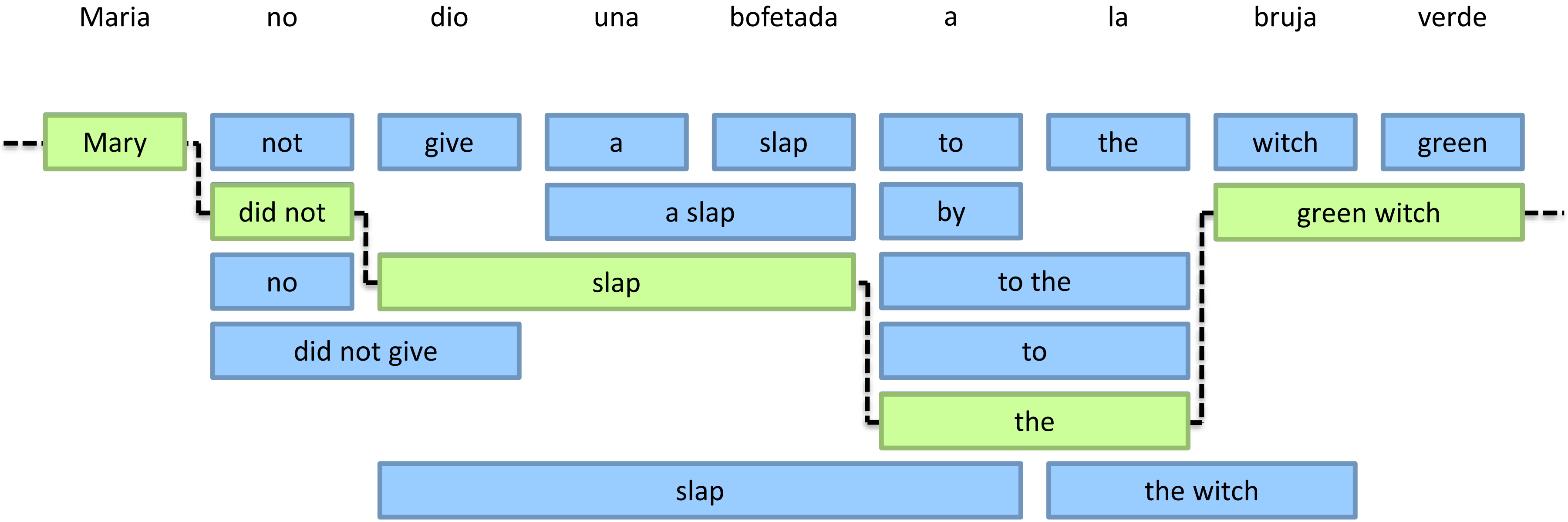
(vi, i saw)
(la mesa pequeña, the small table)
…

maria no daba una bofetada a la bruja verde
Foreign Input Sentence

mary did not slap the green witch
English Output Sentence

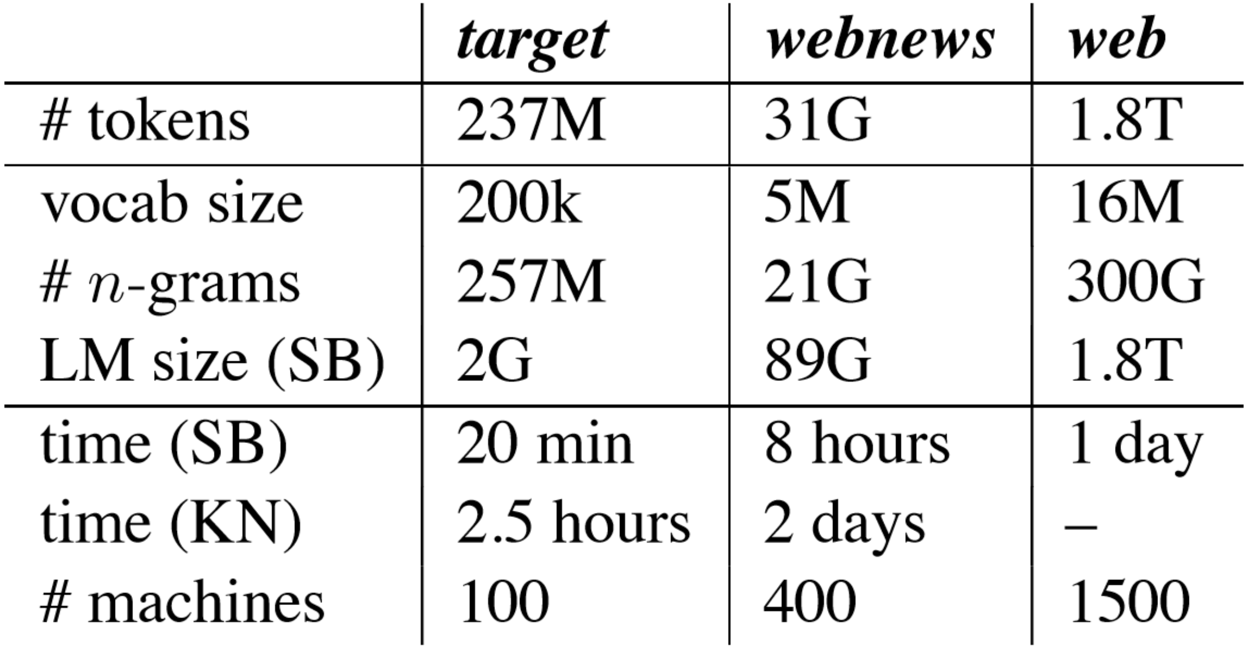
$$\hat{e}_1^I = \arg\max_{e_1^I} \left[P(e_1^I \mid f_1^J) \right] = \arg\max_{e_1^I} \left[P(e_1^I) P(f_1^J \mid e_1^I) \right]$$

Translation as a Tiling Problem



$$\hat{e}_1^I = \arg\max_{e_1^I} \left[P(e_1^I \mid f_1^J) \right] = \arg\max_{e_1^I} \left[P(e_1^I) P(f_1^J \mid e_1^I) \right]$$

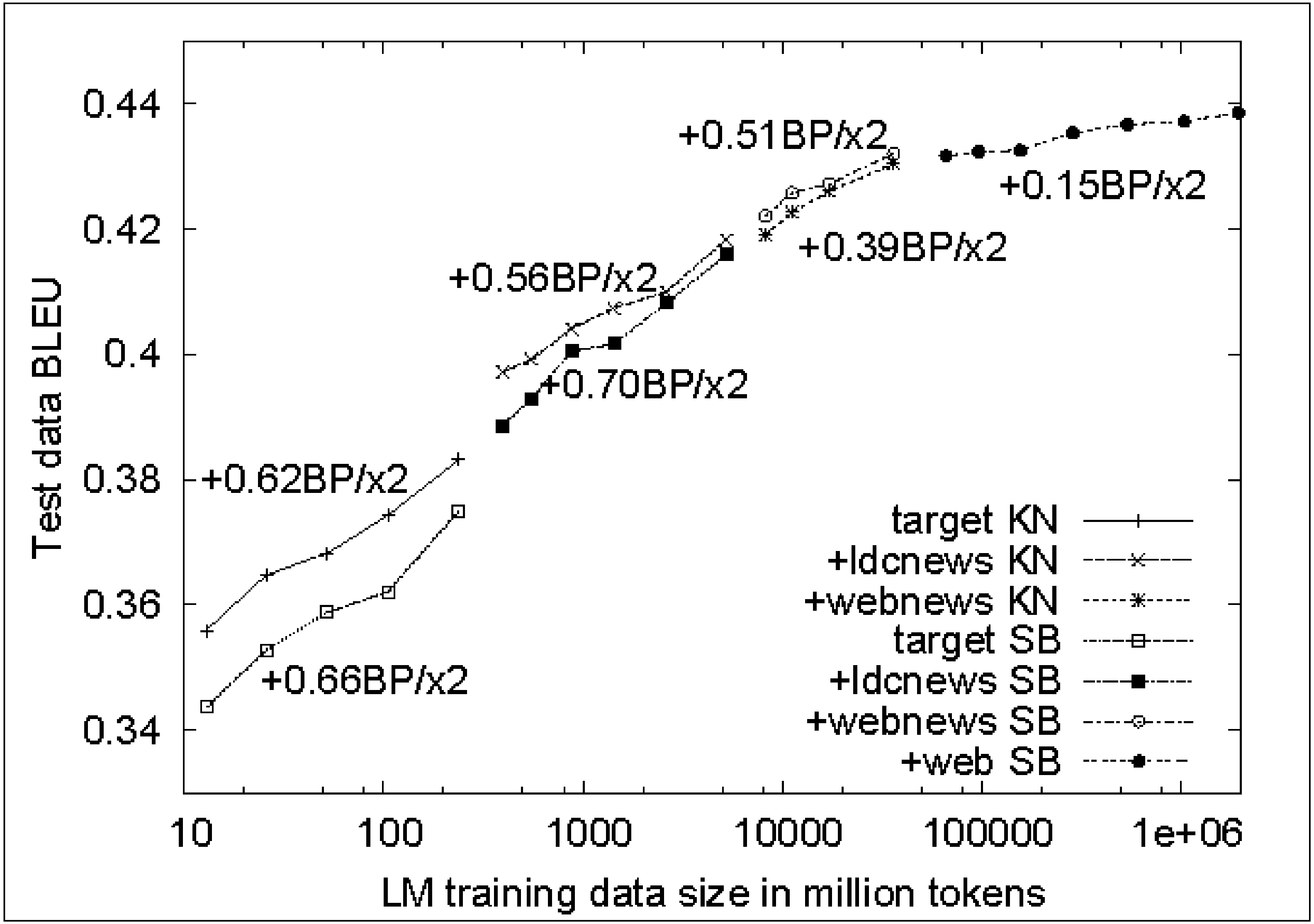
Results: Running Time



	target	*webnews*	*web*
# tokens	237M	31G	1.8T
vocab size	200k	5M	16M
# n-grams	257M	21G	300G
LM size (SB)	2G	89G	1.8T
time (SB)	20 min	8 hours	1 day
time (KN)	2.5 hours	2 days	–
# machines	100	400	1500

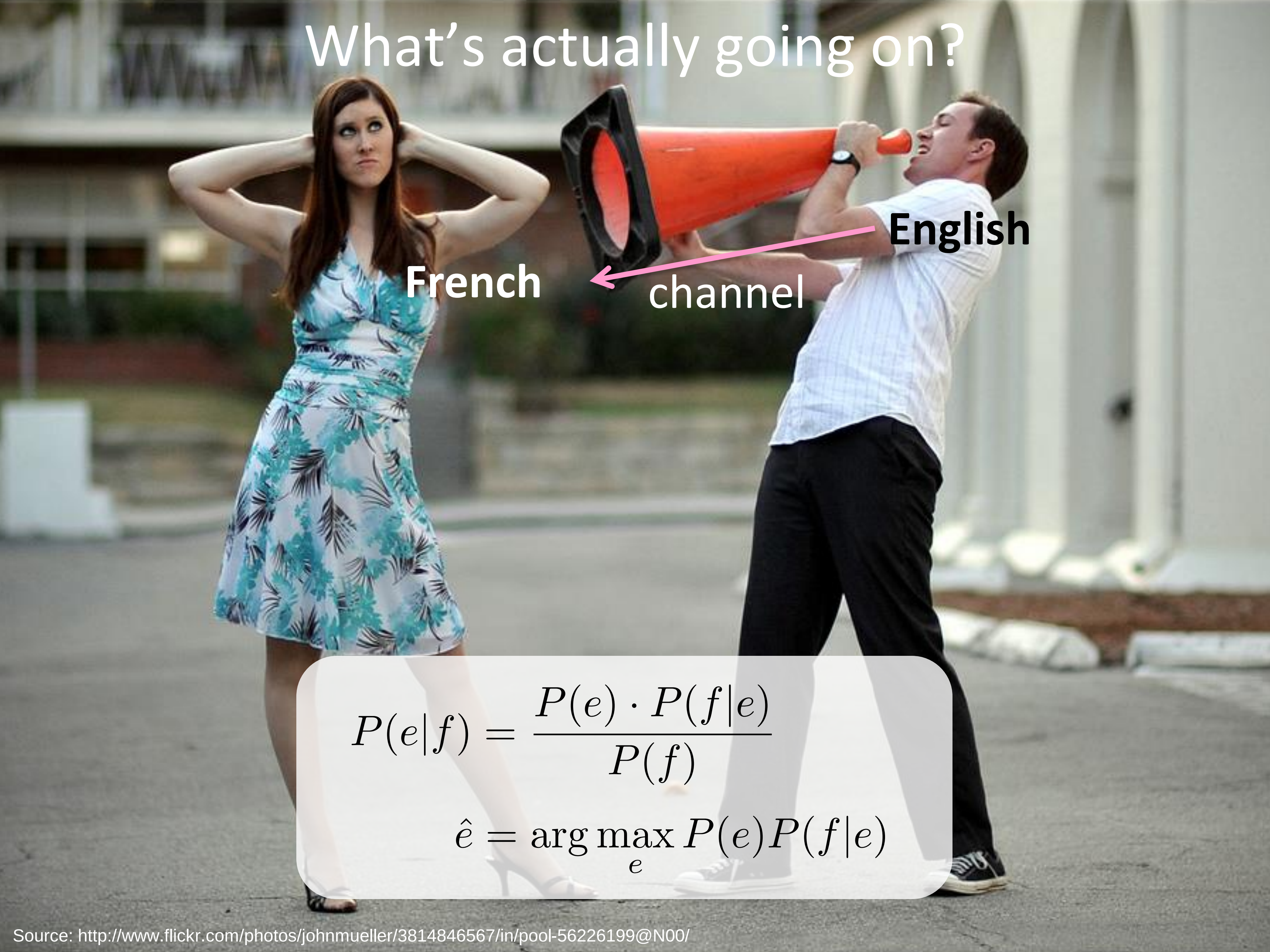
Source: Brants et al. (EMNLP 2007)

Results: Translation Quality



Source: Brants et al. (EMNLP 2007)

What’s actually going on?



English

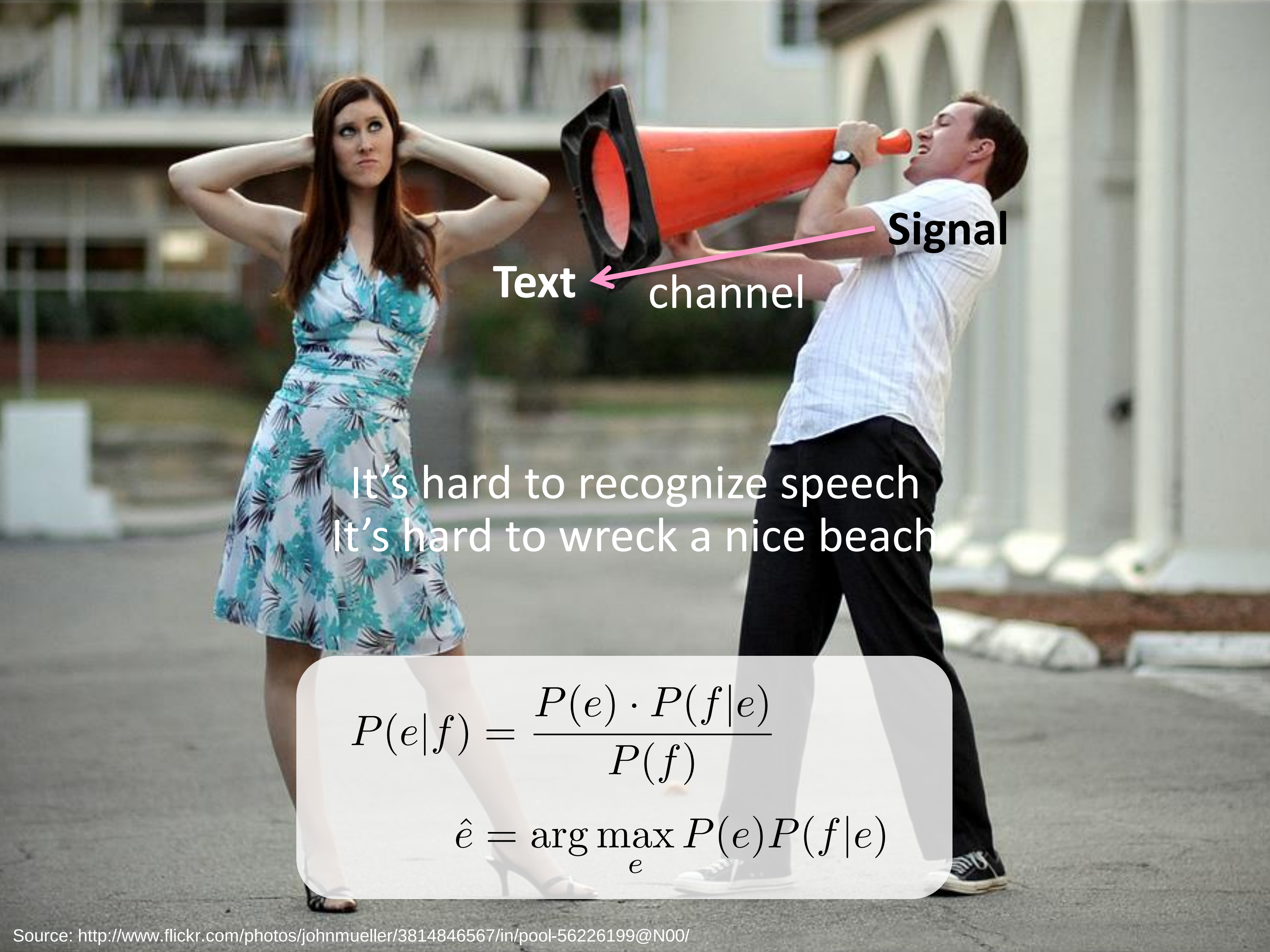
channel

French

$$P(e|f) = \frac{P(e) \cdot P(f|e)}{P(f)}$$

$$\hat{e} = \arg\max_{e} P(e)P(f|e)$$

Source: http://www.flickr.com/photos/johnmueller/3814846567/in/pool-56226199@N00/



Signal

Text

channel

It’s hard to recognize speech
It’s hard to wreck a nice beach

$$P(e|f) = \frac{P(e) \cdot P(f|e)}{P(f)}$$

$$\hat{e} = \arg\max_{e} P(e)P(f|e)$$

Source: http://www.flickr.com/photos/johnmueller/3814846567/in/pool-56226199@N00/

receive

recieve

channel

autocorrect #fail

$$P(e|f) = \frac{P(e) \cdot P(f|e)}{P(f)}$$

$$\hat{e} = \arg\max_{e} P(e)P(f|e)$$

Source: http://www.flickr.com/photos/johnmueller/3814846567/in/pool-56226199@N00/

Neural Networks

Have taken over…

Search!

Source: http://www.flickr.com/photos/guvnah/7861418602/

The Central Problem in Search

Searcher

Author

Concepts ↓ Query Terms

“tragic love story”

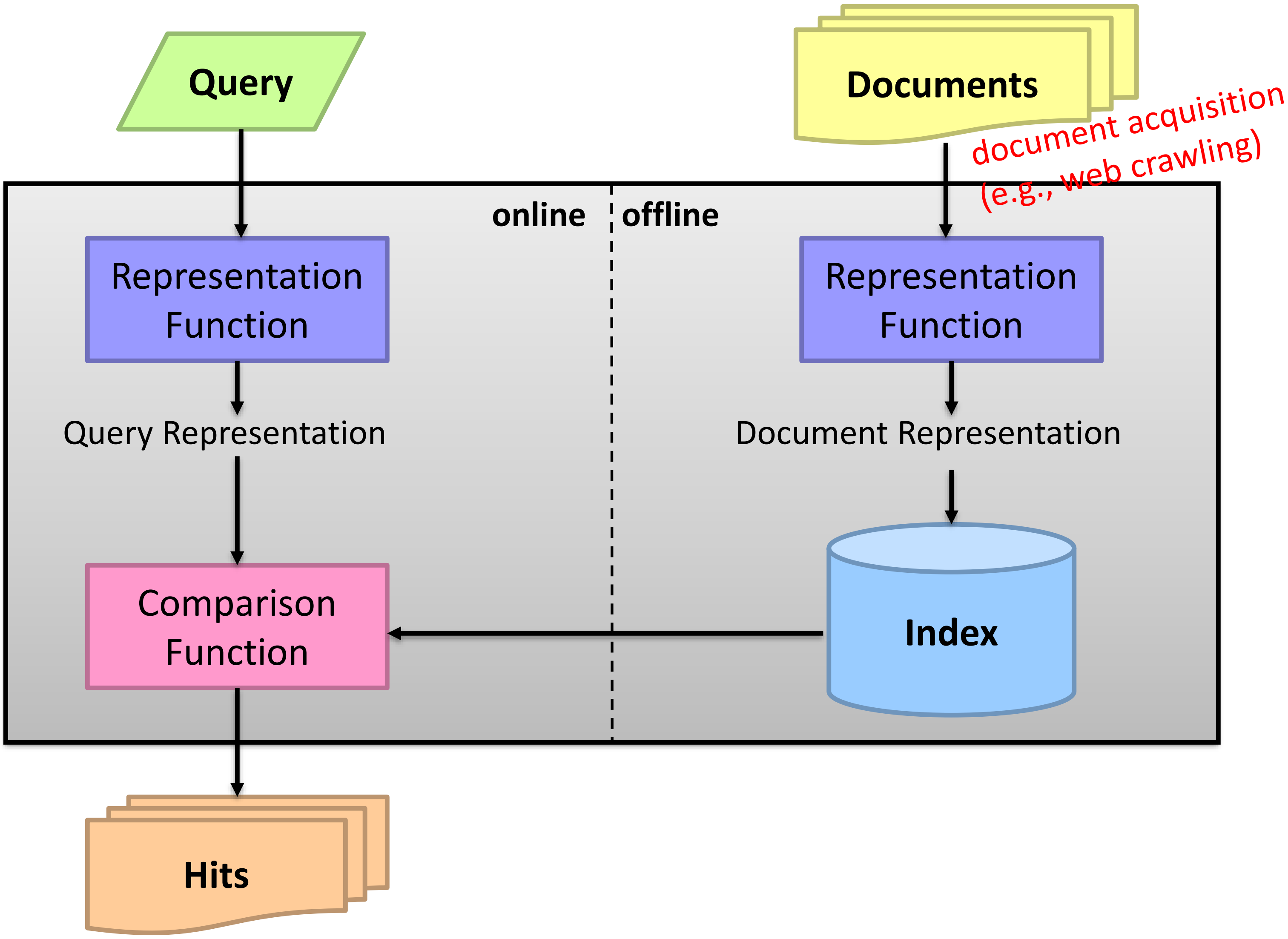
↔

Concepts ↓ Document Terms

“fateful star-crossed romance”

Do these represent the same concepts?

Abstract IR Architecture



How do we represent text?

Remember: computers don’t “understand” anything!

“Bag of words”

Treat all the words in a document as index terms

Assign a “weight” to each term based on “importance”

(or, in simplest case, presence/absence of word)

Disregard order, structure, meaning, etc. of the words

Simple, yet effective!

Assumptions

Term occurrence is independent

Document relevance is independent

“Words” are well-defined

What’s a word?

天主教教宗若望保祿二世因感冒再度住進醫院。
這是他今年第二度因同樣的病因住院。

الناطق باسم -وقال مارك ريجيف
إن شارون قبل -الخارجية الإسرائيلية
الدعوة وسيقوم للمرة الأولى بزيارة
تونس، التي كانت لفترة طويلة المقر
1982.الرسمي لمنظمة التحرير الفلسطينية بعد خروجها من لبنان عام

Выступая в Мещанском суде Москвы экс-глава ЮКОСа
заявил не совершал ничего противозаконного, в чем
обвиняет его генпрокуратура России.

भारत सरकार ने आर्थिक सर्वेक्षण में वित्तीय वर्ष 2005-06 में सात फ़ीसदी
विकास दर हासिल करने का आकलन किया है और कर सुधार पर ज़ोर
दिया है

日米連合で台頭中国に対処…アーミテージ前副長官提言

조재영 기자= 서울시는 25일 이명박 시장이 `행정중심복합도시'' 건설안
에 대해 `군대라도 동원해 막고싶은 심정''이라고 말했다는 일부 언론의
보도를 부인했다.

Sample Document

McDonald's slims down spuds

Fast-food chain to reduce certain types of fat in its french fries with new cooking oil.

NEW YORK (CNN/Money) - McDonald's Corp. is cutting the amount of "bad" fat in its french fries nearly in half, the fast-food chain said Tuesday as it moves to make all its fried menu items healthier.

But does that mean the popular shoestring fries won't taste the same? The company says no. "It's a win-win for our customers because they are getting the same great french-fry taste along with an even healthier nutrition profile," said Mike Roberts, president of McDonald's USA.

But others are not so sure. McDonald's will not specifically discuss the kind of oil it plans to use, but at least one nutrition expert says playing with the formula could mean a different taste.

Shares of Oak Brook, Ill.-based McDonald's (MCD: down $0.54 to $23.22, Research, Estimates) were lower Tuesday afternoon. It was unclear Tuesday whether competitors Burger King and Wendy's International (WEN: down $0.80 to $34.91, Research, Estimates) would follow suit. Neither company could immediately be reached for comment.

…

“Bag of Words”

14 × McDonalds

12 × fat

11 × fries

8 × new

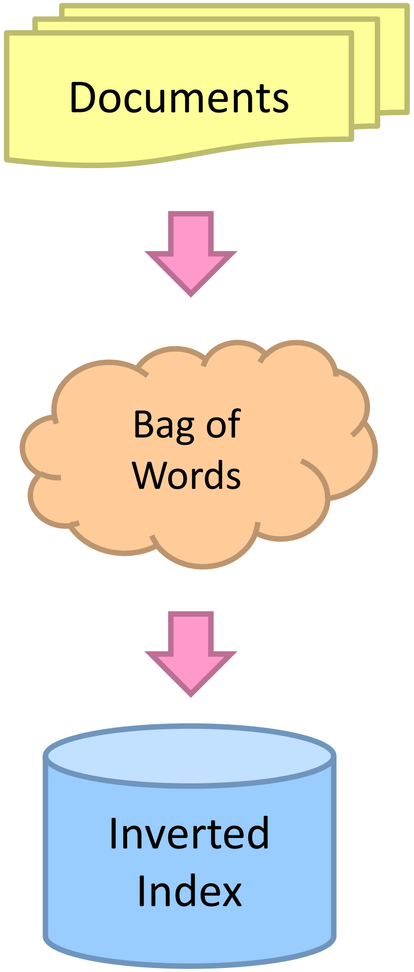
7 × french

6 × company, said, nutrition

5 × food, oil, percent, reduce, taste, Tuesday

…

Counting Words…



Documents

Bag of Words

Inverted Index

case folding, tokenization, stopword removal, stemming

~~syntax~~, ~~semantics~~, word ~~knowledge~~, etc.

Count.

Source: http://www.flickr.com/photos/guvnah/7861418602/

Doc 1
one fish, two fish

Doc 2
red fish, blue fish

Doc 3
cat in the hat

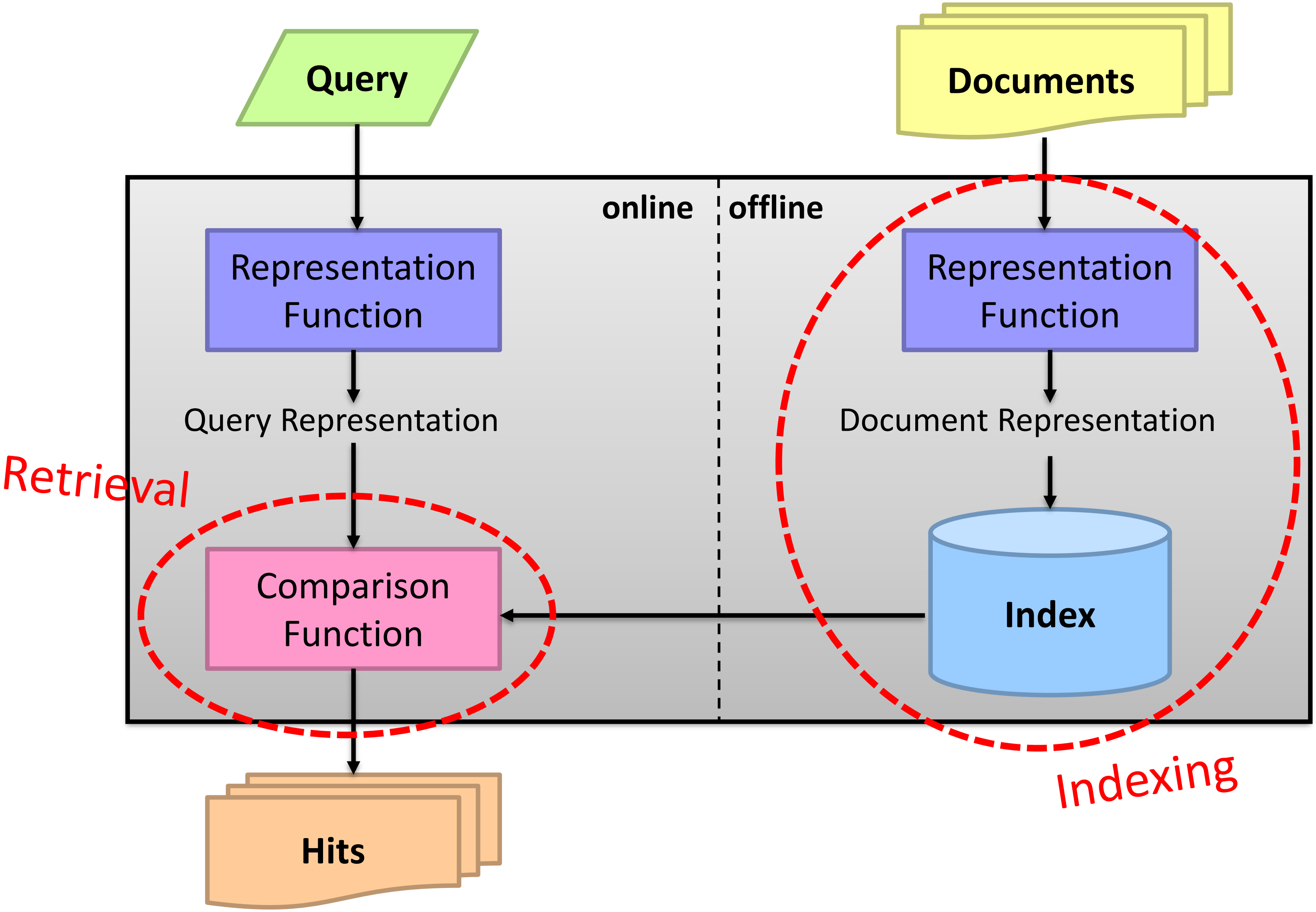
Doc 4
green eggs and ham

	1	2	3	4
blue		1		
cat			1	
egg				1
fish	1	1		
green				1
ham				1
hat			1	
one	1			
red		1		
two	1			

What goes in each cell?

boolean
count
positions

Abstract IR Architecture



Doc 1
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Doc 4
green eggs and ham

	1	2	3	4
blue		1		
cat			1	
egg				1
fish	1	1		
green				1
ham				1
hat			1	
one	1			
red		1		
two	1			

Indexing: building this structure

Retrieval: manipulating this structure

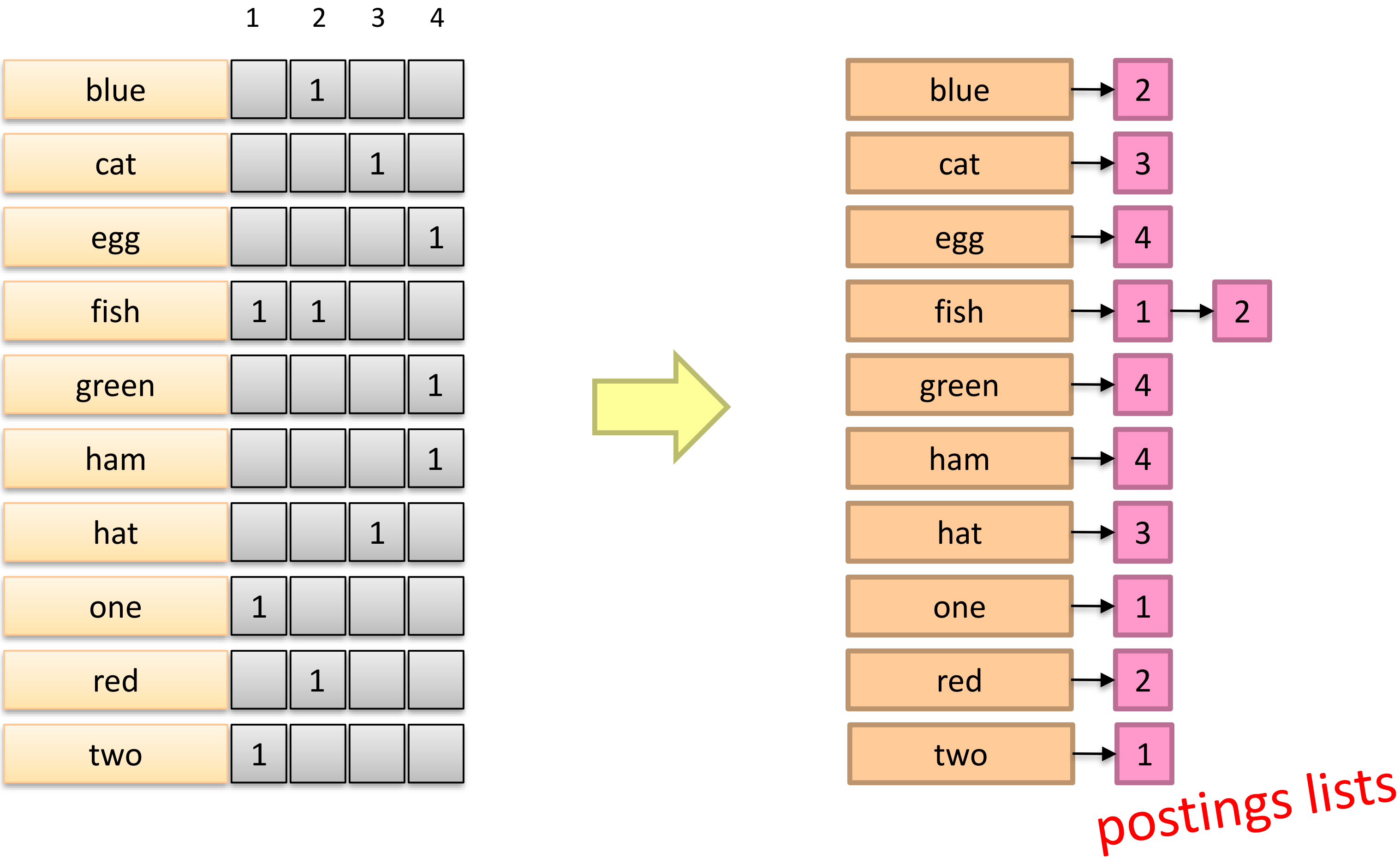
Where have we seen this before?

Doc 1
one fish, two fish

Doc 2
red fish, blue fish

Doc 3
cat in the hat

Doc 4
green eggs and ham



	1	2	3	4
blue		1		
cat			1	
egg				1
fish	1	1		
green				1
ham				1
hat			1	
one	1			
red		1		
two	1			

blue → 2
cat → 3
egg → 4
fish → 1 → 2
green → 4
ham → 4
hat → 3
one → 1
red → 2
two → 1

postings lists

Indexing: Performance Analysis

Fundamentally, a large sorting problem

Terms usually fit in memory

Postings usually don’t

How is it done on a single machine?

How can it be done with MapReduce?

First, let’s characterize the problem size:

Size of vocabulary

Size of postings

Vocabulary Size: Heaps' Law

$$M = kT^b$$

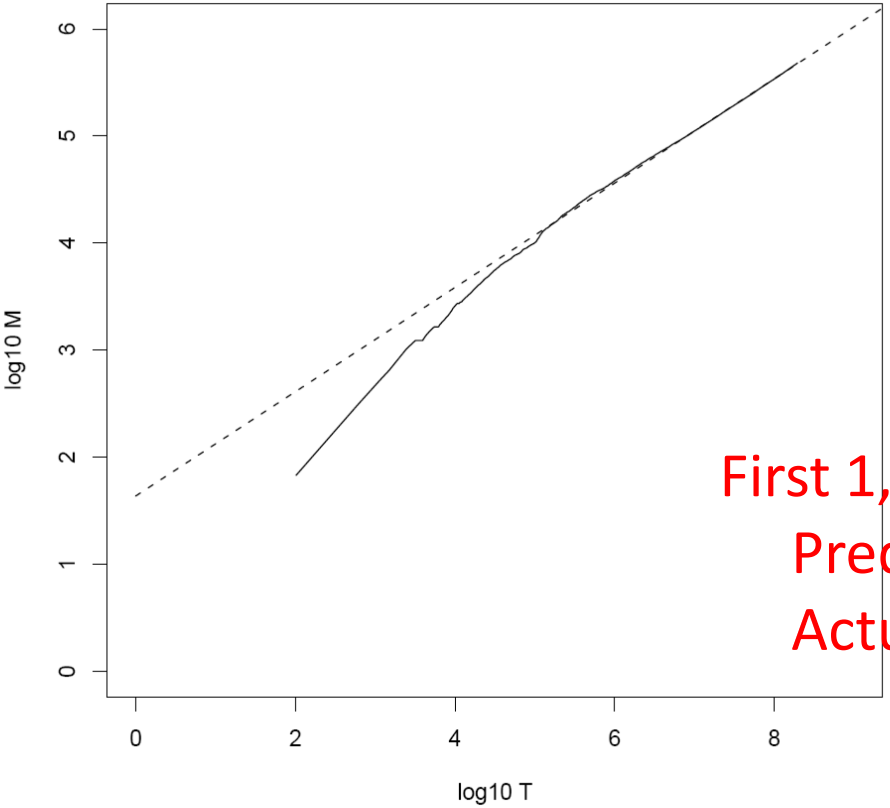
M is vocabulary size
T is collection size (number of documents)
k and *b* are constants

Typically, *k* is between 30 and 100, *b* is between 0.4 and 0.6

Heaps' Law: linear in log-log space

Surprise: Vocabulary size grows unbounded!

Heaps' Law for RCV1



k = 44

b = 0.49

First 1,000,020 terms:

Predicted = 38,323

Actual = 38,365

Reuters-RCV1 collection: 806,791 newswire documents (Aug 20, 1996-August 19, 1997)

Manning, Raghavan, Schütze, Introduction to Information Retrieval (2008)

Postings Size: Zipf’s Law

$$f(k; s, N) = \frac{1/k^s}{\sum_{n=1}^{N} (1/n^s)}$$

N	number of elements
k	rank
s	characteristic exponent

Zipf’s Law: (also) linear in log-log space

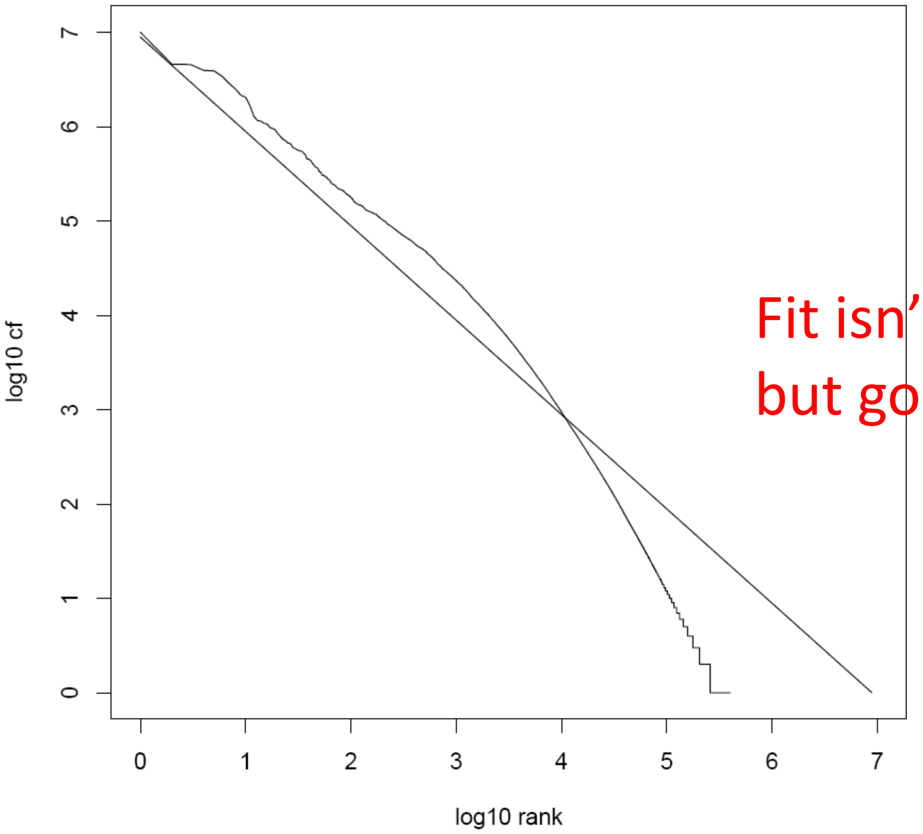
Specific case of Power Law distributions

In other words:

A few elements occur very frequently

Many elements occur very infrequently

Zipf’s Law for RCV1

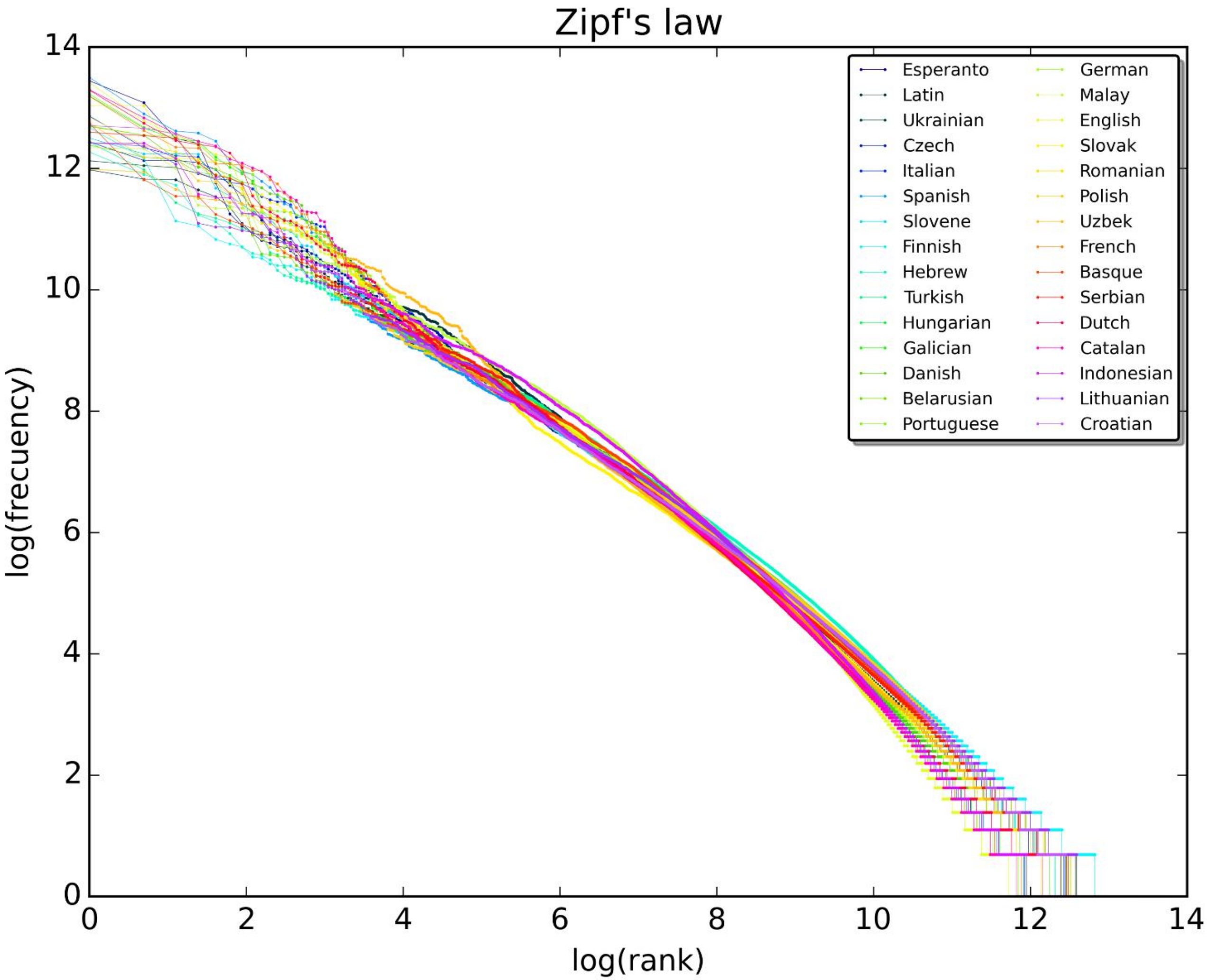


Fit isn’t that good… but good enough!

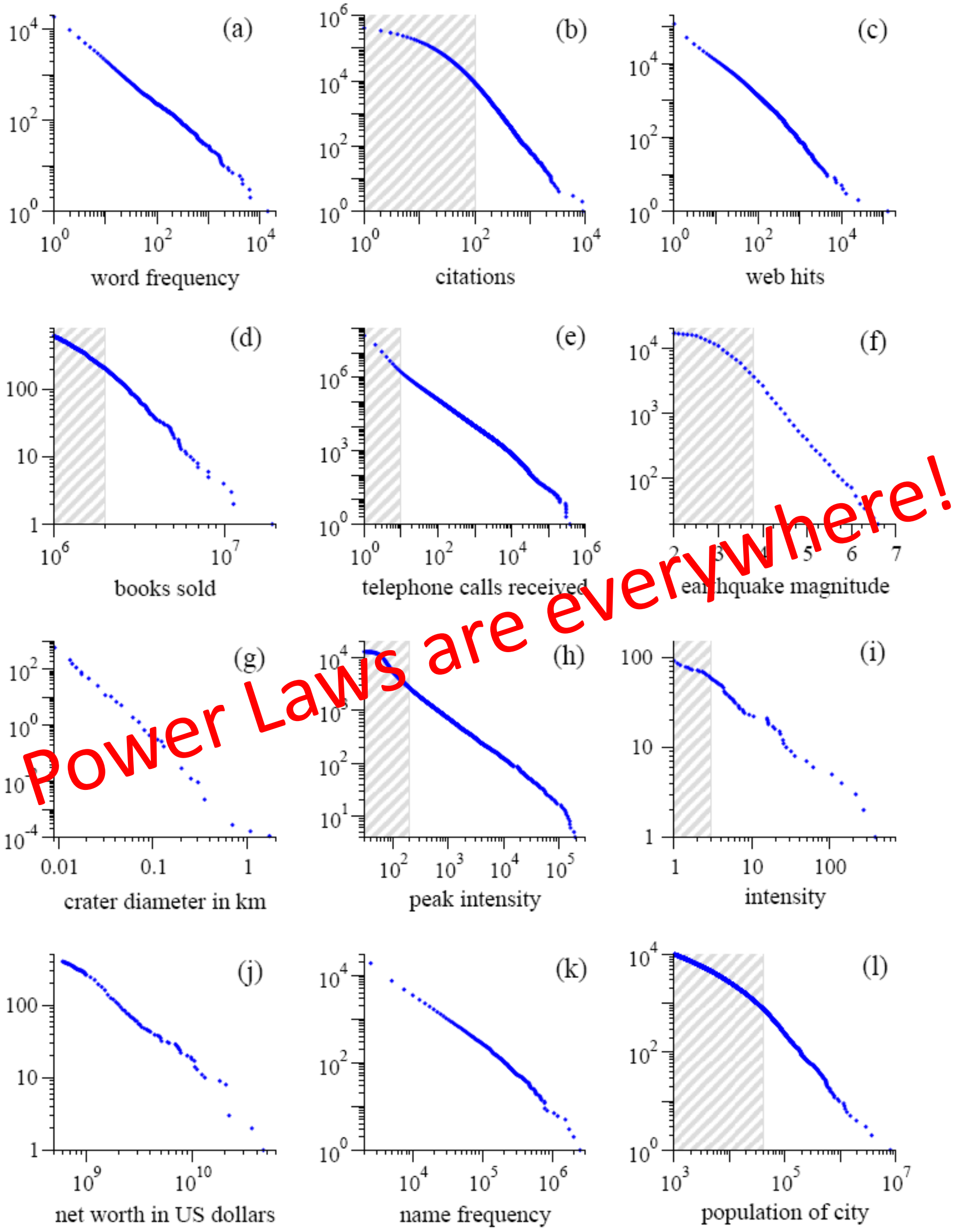
Reuters-RCV1 collection: 806,791 newswire documents (Aug 20, 1996-August 19, 1997)

Manning, Raghavan, Schütze, Introduction to Information Retrieval (2008)

Zipf’s Law for Wikipedia



Rank versus frequency for the first 10m words in 30 Wikipedias (dumps from October 2015)



Power Laws are everywhere!

Figure from: Newman, M. E. J. (2005) “Power laws, Pareto distributions and Zipf's law.” Contemporary Physics 46:323–351.

MapReduce: Index Construction

Map over all documents

Emit *term* as key, (*docid*, *tf*) as value

Emit other information as necessary (e.g., term position)

Sort/shuffle: group postings by term

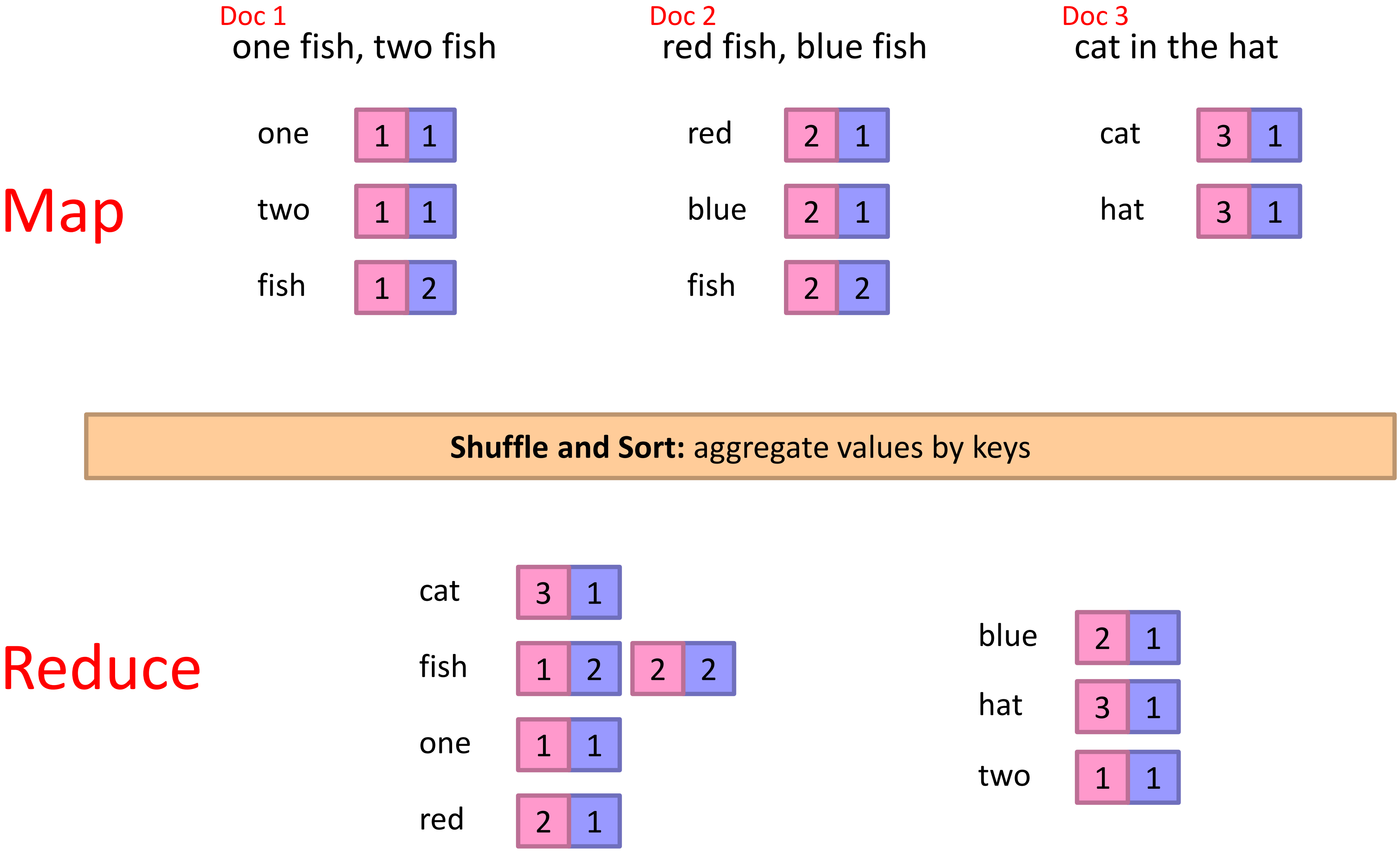
Reduce

Gather and sort the postings (typically by *docid*)

Write postings to disk

MapReduce does all the heavy lifting!

Inverted Indexing with MapReduce



Map

Doc 1
one fish, two fish

one	1	1
two	1	1
fish	1	2

Doc 2
red fish, blue fish

red	2	1
blue	2	1
fish	2	2

Doc 3
cat in the hat

cat	3	1
hat	3	1

Shuffle and Sort: aggregate values by keys

Reduce

cat	3	1		
fish	1	2	2	2
one	1	1		
red	2	1		

blue	2	1
hat	3	1
two	1	1

Inverted Indexing: Pseudo-Code

```
class Mapper {
  def map(docid: Long, doc: String) = {
    val counts = new Map()
    for (term <- tokenize(doc)) {
      counts(term) += 1
    }
    for ((term, tf) <- counts) {
      emit(term, (docid, tf))
    }
  }
}

class Reducer {
  def reduce(term: String, postings: Iterable[(docid, tf)]) = {
    val p = new List()
    for ((docid, tf) <- postings) {
      p.append((docid, tf))
    }
    p.sort()
    emit(term, p)
  }
}
```

What’s the problem?

Stay tuned…

Source: Wikipedia (Japanese rock garden)