67-300 SEARCH ENGINES

LANGUAGE MODEL

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LECTURE GOALS

- Missing notes on floating representation in a computer
- Language Model
- Discussion on Homework
- Implementation Part (IPython notebook) - If we have time

FLOATING PRECISION AND LOGARITHM

LOG TRANSFORMATION

- Floating-point numbers are represented in base 2 fraction.
  - 0.125 => 1/10 + 2/100 + 5/1000 (human representation)
  - 0.125 => 0/2 + 0/4 + 1/8 (computer representation)
- Not precise, best approximation with 53 bits for precision
- How good is the human representation/precision for 1/3?
  - 0.3?
  - 0.333?
  - 0.3333333?

PRECISION LIMITED

```
In [1]: 1./3
Out[1]: 0.3333333333333333

In [2]: print "%.100f" % (1./3)
0.333333333333333314829616256247390992939472198486328125000000000000000

In [3]: 1/3. > 0.3333333333333332
Out[3]: True

In [4]: 1/3. > 0.33333333333333332
Out[4]: False

In [5]: 1/3. == 0.3333333333333333
Out[5]: True

In [6]: 1/3. == 0.3333333333333332
Out[6]: False

In [7]: 1/3. == 0.33333333333333332
Out[7]: True
```

PRECISION LIMITED

```
In [1]: 0.1
Out[1]: 0.1

In [2]: 0.1 + 0.1
Out[2]: 0.2

In [3]: 0.1 + 0.1 + 0.1
Out[3]: 0.30000000000000004

In [4]: 0.3 == 0.1 + 0.1 + 0.1
Out[4]: False
```

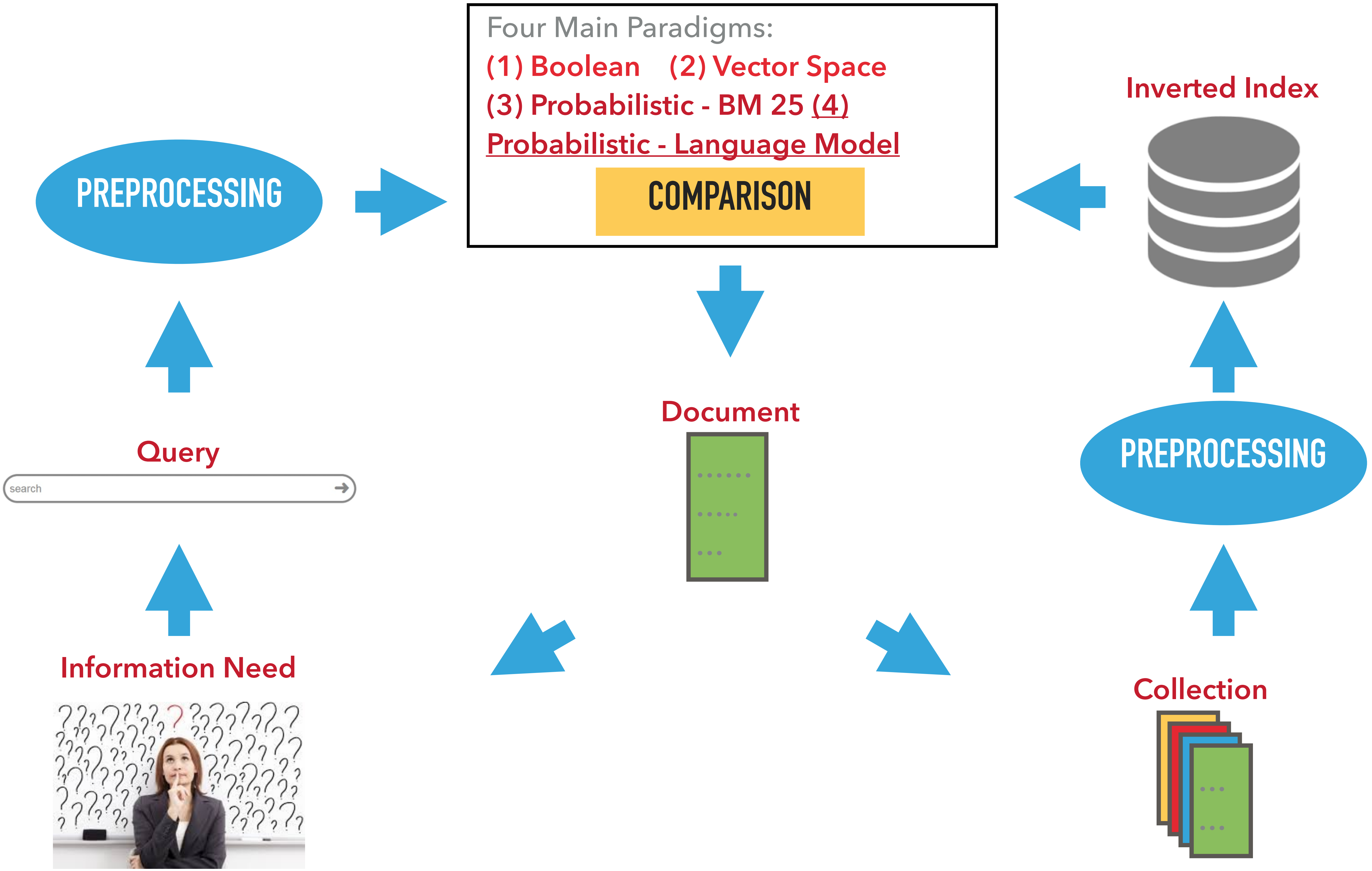
PRECISION LIMITED

$$RSV = \log \prod_{x_i=1; q_i=1} \frac{p_i \times (1 - r_i)}{r_i \times (1 - p_i)} = \sum_{x_i=1; q_i=1} \log \frac{p_i \times (1 - r_i)}{r_i \times (1 - p_i)}$$

```
In [33]: 1e-10 * 1e-10
Out[33]: 1.0000000000000001e-20

In [34]: 1e-10 * 1e-10 > 1e-20
Out[34]: True

In [35]: math.log(1e-10) + math.log(1e-10) > math.log(1e-20)
Out[35]: False

In [36]: math.log(1e-10) + math.log(1e-10) < math.log(1e-20)
Out[36]: False

In [37]: math.log(1e-10) + math.log(1e-10) == math.log(1e-20)
Out[37]: True
```

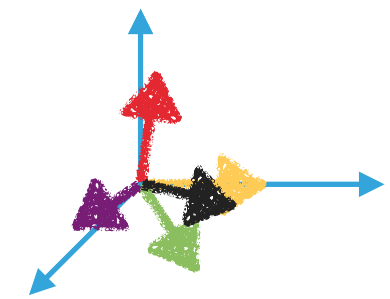
CHANGING FROM PRODUCT TO SUM ALLEVIATE PRECISION PROBLEMS, AMONG OTHER ADVANTAGES.

CLASS 5 - LANGUAGE MODEL



RECAP: BIM

FRAMEWORKS RECAP

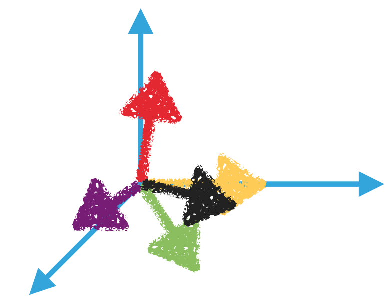


- VSM: strong geometric motivation
- Probabilistic framework: $P(R_{d,q} = 1|d, q)$
  - Binary Independence Model

document	relevant (R=1)	nonrelevant(R=0)
term present x_i = 1	p_i	r_i
term absent x_i=0	1-p_i	1-r_i

$$O(R|q,x) = \frac{P(R=1|q,x)}{P(R=0|q,x)} = \sum_{i}^{|V|} \boxed{\frac{p_i}{r_i \cdot}} \times \boxed{\frac{(1-r_i)}{(1-p_i)}}$$

FRAMEWORKS RECAP



- VSM: strong geometric motivation
- Probabilistic framework: $P(R_{d,q} = 1|d, q)$
  - Binary Independence Model

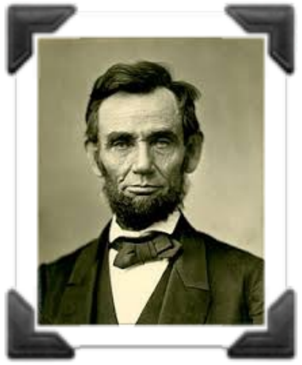
document	relevant (R=1)	nonrelevant(R=0)
term present $x_i = 1$	p_i	r_i
term absent $x_i=0$	$1-p_i$	$1-r_i$

$$O(R|q,x) = \frac{P(R=1|q,x)}{P(R=0|q,x)} = \sum_{i}^{|V|} \boxed{\frac{p_i}{r_i}} \times \boxed{\frac{(1-r_i)}{(1-p_i)}}$$

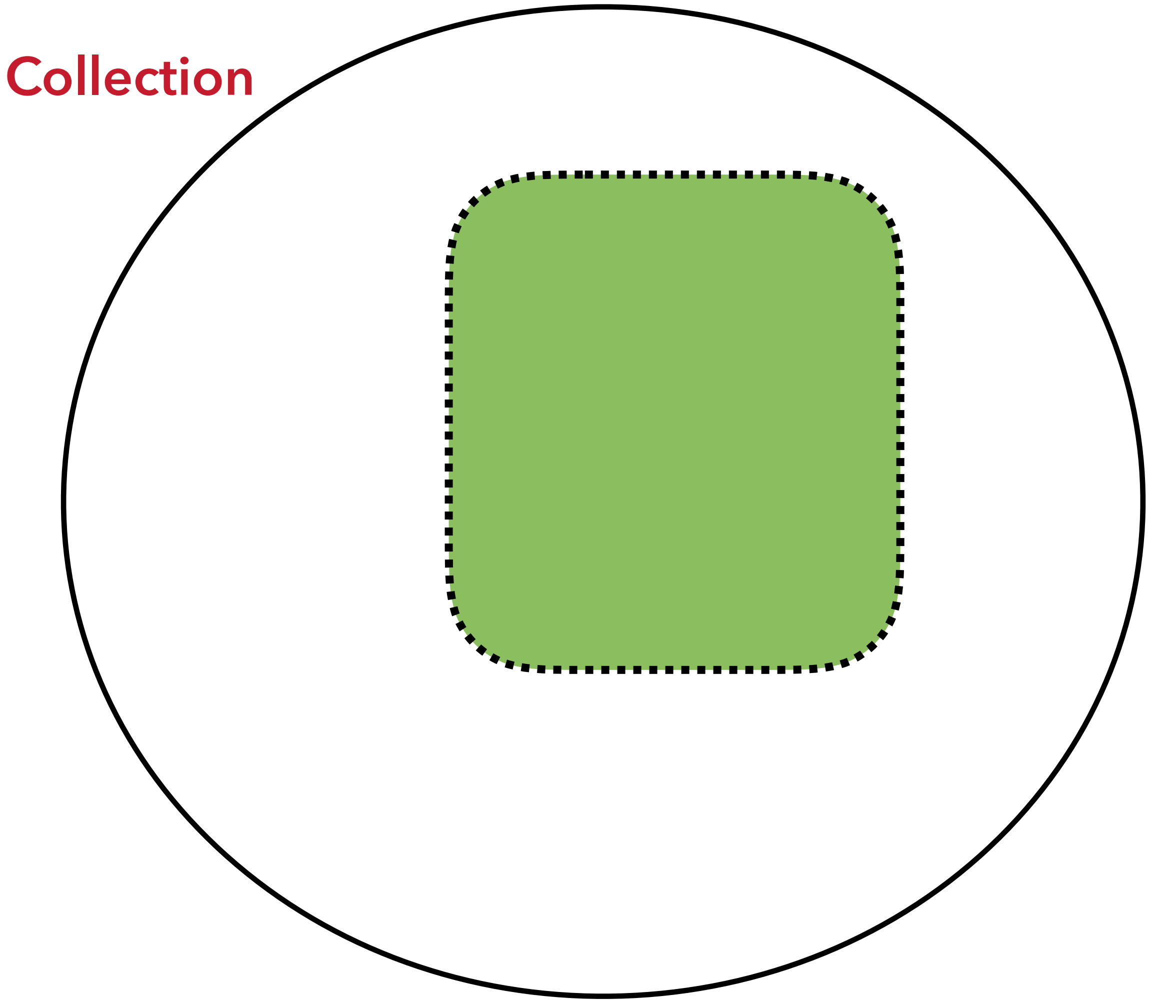
Term i is in this document.
How much certainty are we that this is a relevant doc?

Term i is NOT in this document.
How much certainty are we that this is a relevant doc?

BIM AND LINCOLN

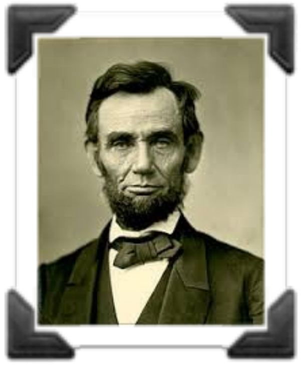


- Query: "lincoln"



- Retrieve all documents that contain "lincoln"
- No values for p_i. Only sort docs by IDF only
- All document have the same score!

BIM AND LINCOLN



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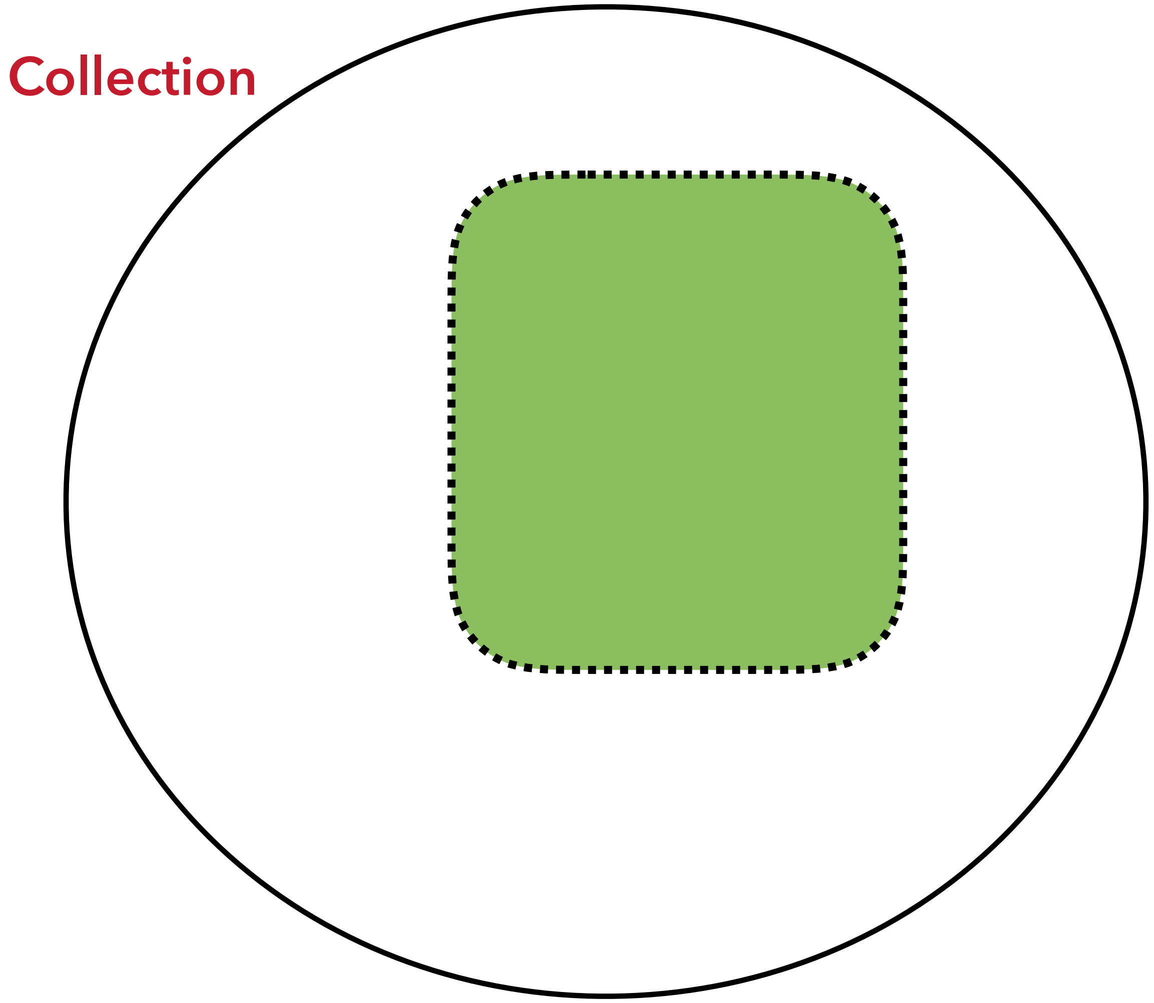


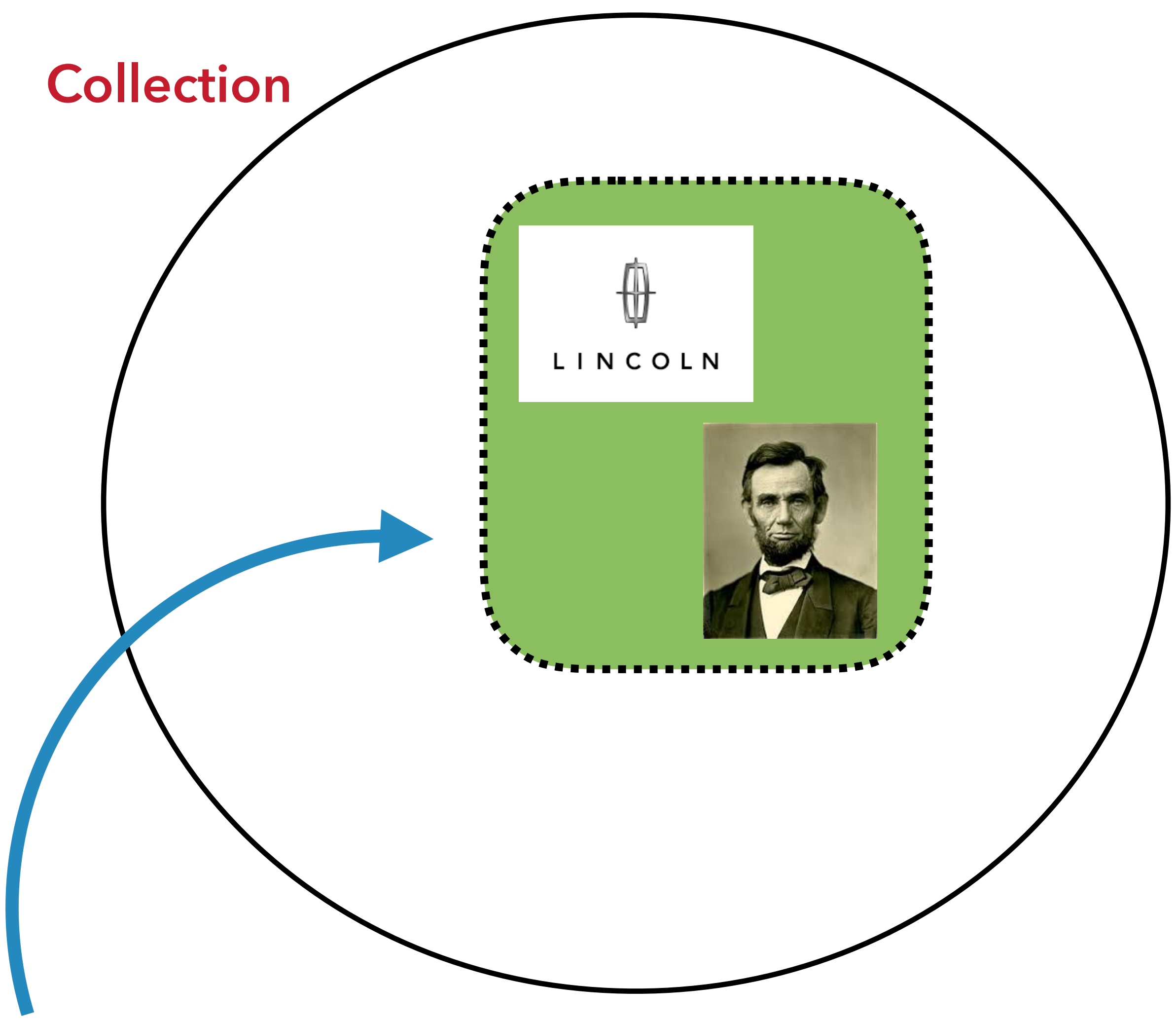
- Retrieve all documents that contain “lincoln”
- No values for p_i. Only sort docs by IDF only
- All document have the same score!

Can you tell me why?

Is it the same output of a Boolean search??

BIM AND LINCOLN

- Query: “lincoln”



Not all documents are relevant!

- Retrieve all documents that contain “lincoln”
- No values for p_i. Only sort docs by IDF only
- All document have the same score!

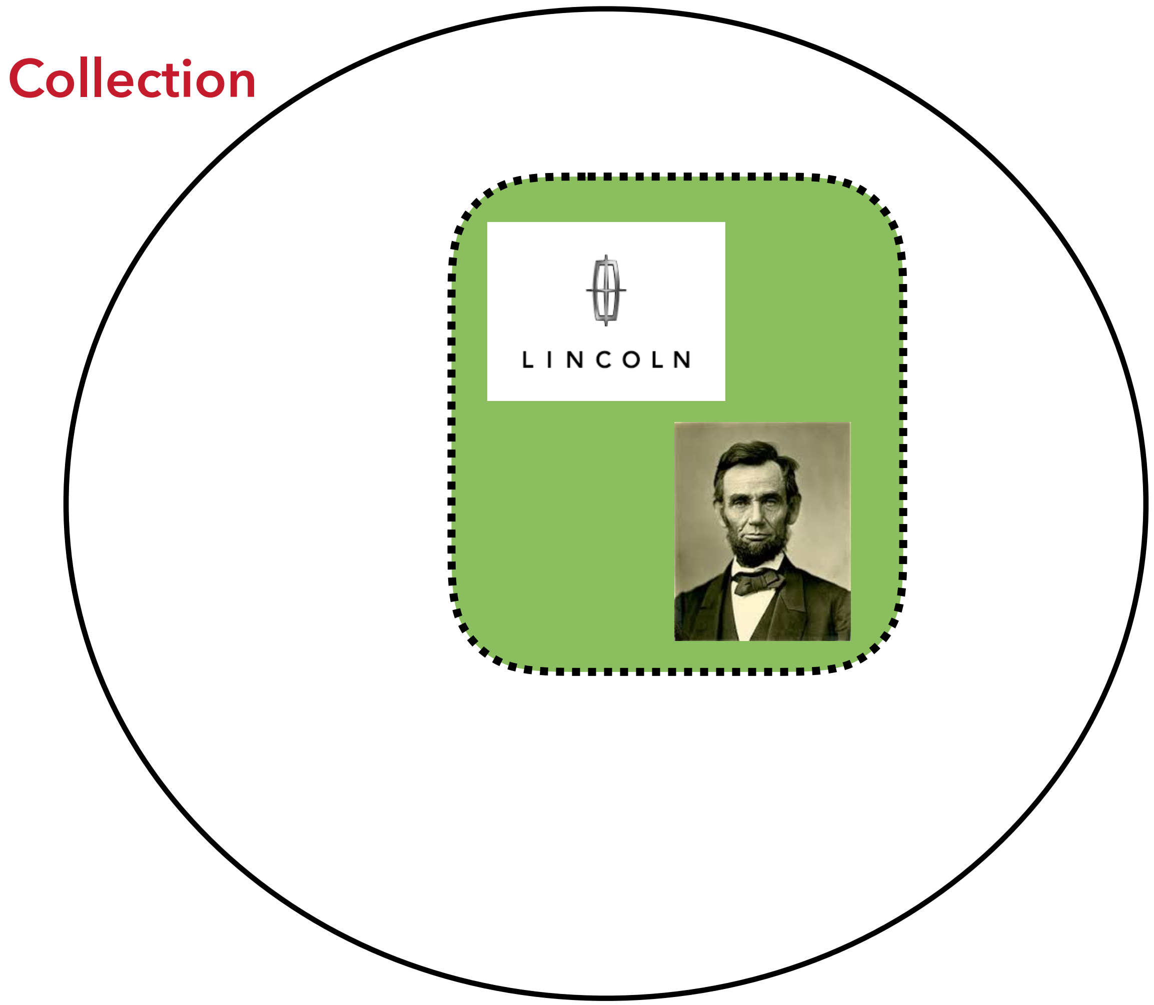
Can you tell me why?

Is it the same output of a Boolean search??

BIM AND LINCOLN

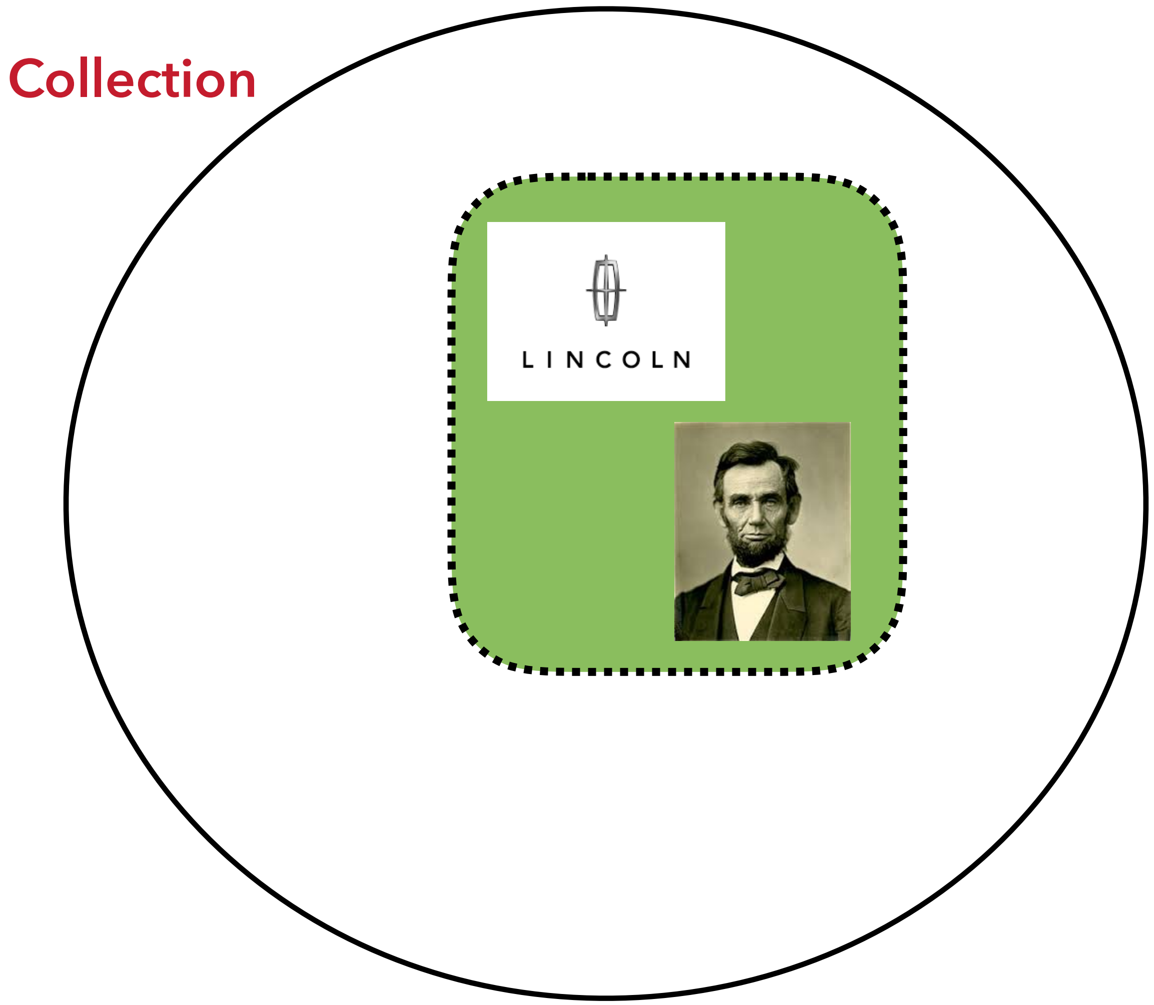
- Query: “lincoln”

- User reads some documents and state that he/she wants documents like **D_i and D_j**



BIM AND LINCOLN

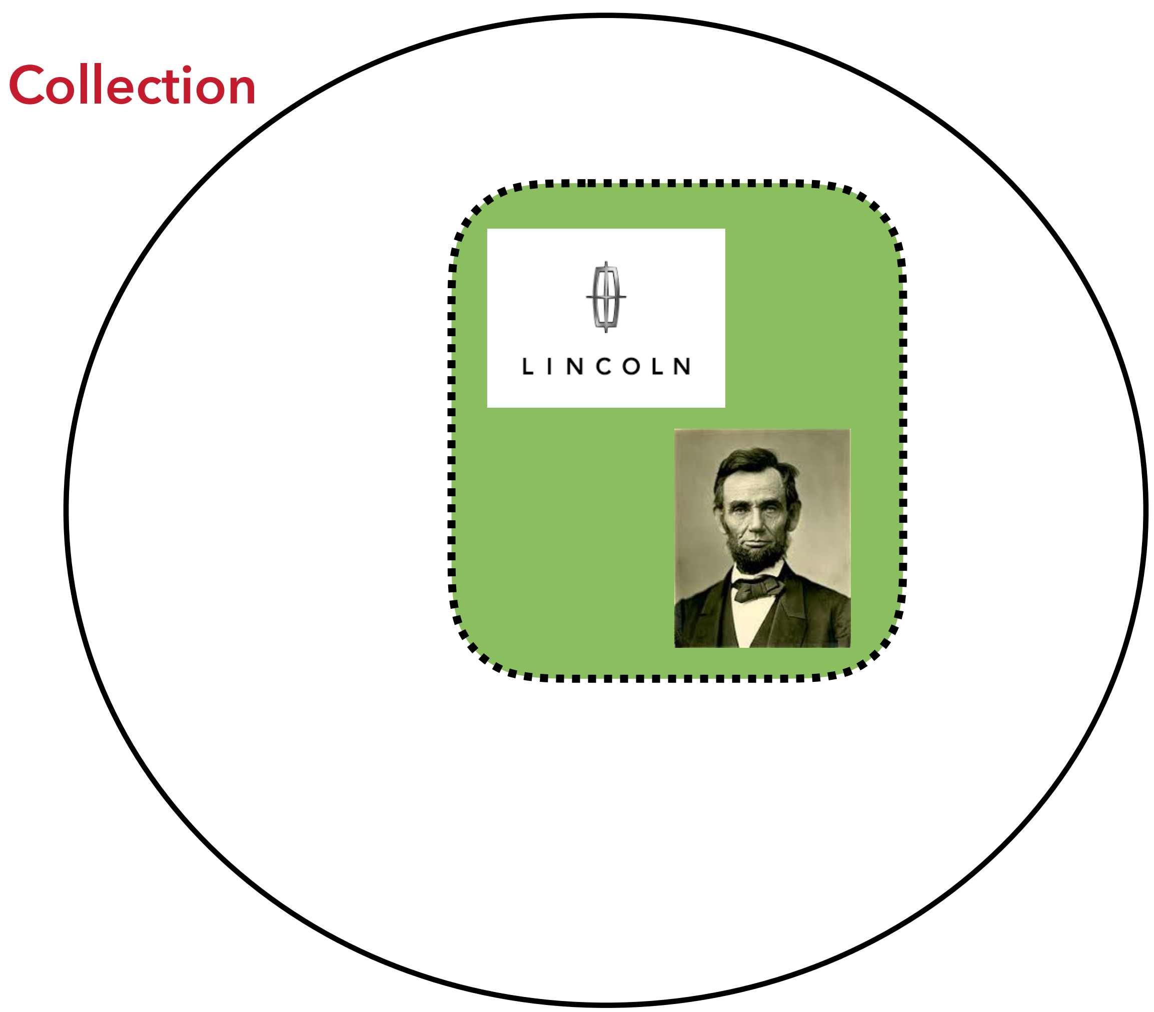
- Query: “lincoln”



- User reads some documents and state that he/she wants documents like **D_i and D_j**
- Algorithm inspects terms in document D_i, D_j
  - Terms from the relevant documents: life, bio, gettysburgh…

BIM AND LINCOLN

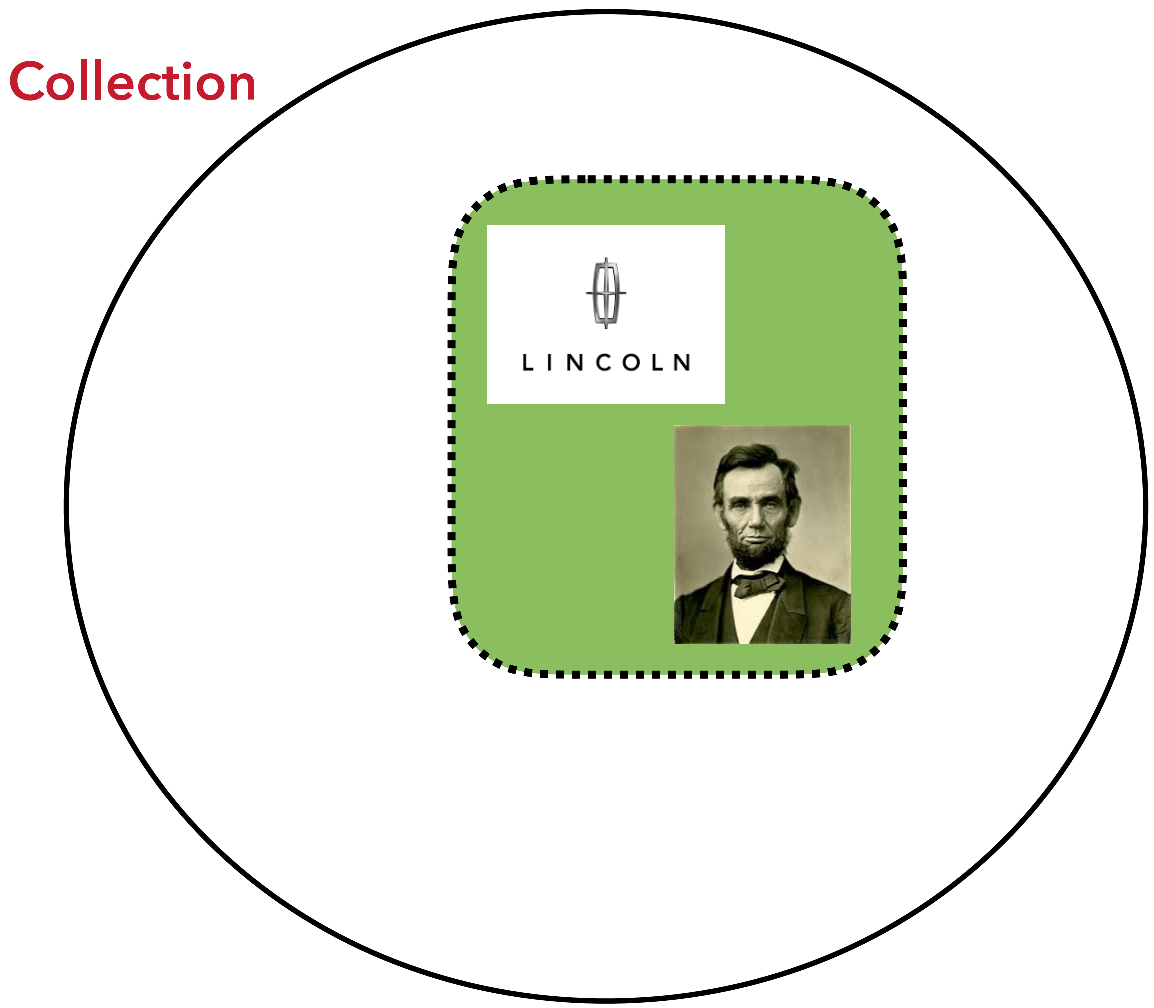
- Query: “lincoln”



- User reads some documents and state that he/she wants documents like **D_i and D_j**
- Algorithm inspects terms in document D_i, D_j
  - Terms from the relevant documents: life, bio, gettysburgh…
- Algorithm inspects terms in all other documents
  - Terms from the non relevant documents: car, automobile…

BIM AND LINCOLN

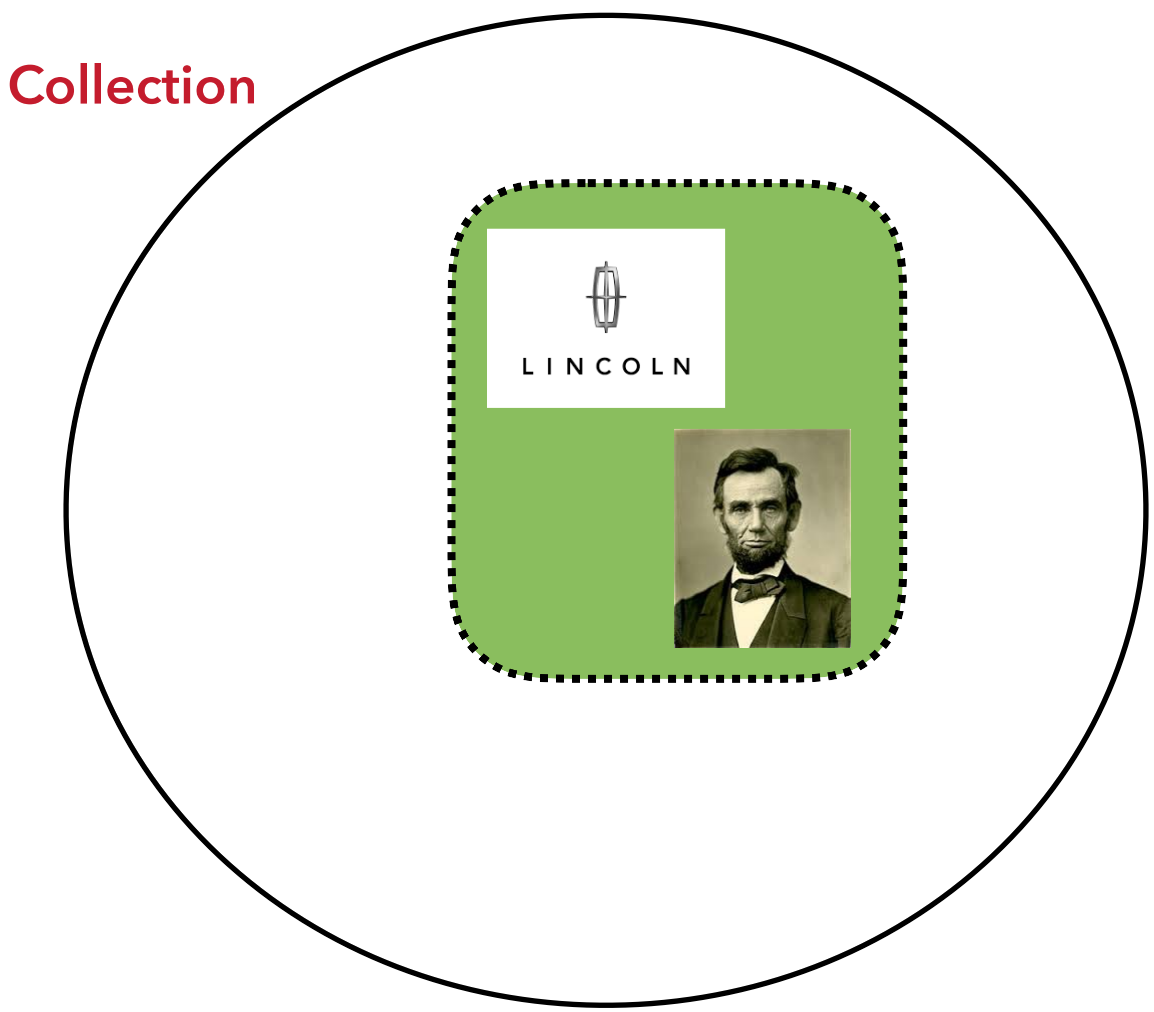
- Query: “lincoln”



- For every term t, what is the likelihood of t being present in relevant docs Vs. being present in non relevant docs.

BIM AND LINCOLN

- Query: “lincoln”



- For every term t, what is the likelihood of t being present in relevant docs Vs. being present in non relevant docs.
- Term: “biography”
  - What is P(R = 1 | “biography”) ?
  - What is P(R = 0 | “biography”) ?
- Term: “industry”
  - What is P(R = 1 | “industry”) ?
  - What is P(R = 0 | “industry”) ?

BM25

$$P(R_{d,q} = 1 | d, q)$$

- Empirical way to instantiate the probabilistic framework
- Removed binary assumption from BIM

$$RSV_d = \sum_{t \in q} \boxed{\log\left[\frac{N}{df_t}\right]} \cdot \boxed{\frac{(k_1+1)tf_{td}}{k_1 \boxed{((1-b) + b \times (L_d/L_{ave}))} + tf_{td}} \cdot \frac{(k_3+1)tf_{tq}}{k_3 + tf_{tq}}}$$

IDF

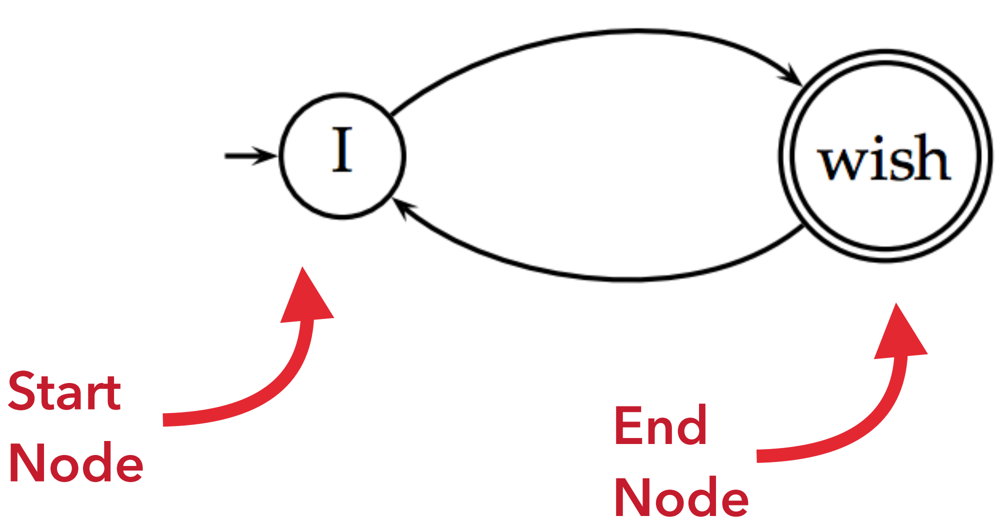
Document Length

TF

LANGUAGE MODELS

LANGUAGE MODELS

- Statistical natural language processing approach.
- Generative model:
  - Let M_d be the language model define by this finite automaton:



I wish

I wish I wish

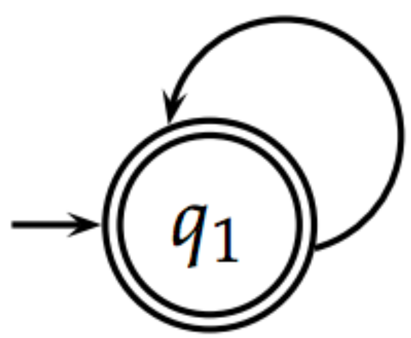
I wish I wish I wish

I wish I wish I wish.....

I wish I?

GENERATIVE MODEL

- How about this other M_d:



$P(\text{STOP}|q_1) = 0.2$

the	0.2
a	0.1
frog	0.01
toad	0.01
said	0.03
likes	0.02
that	0.04
...	...

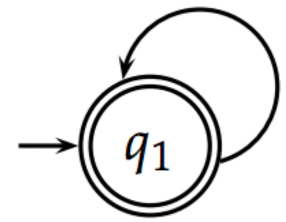
Probabilities sum to 1

$$\sum_{t \in L} P(t) = 1$$

- P(frog said that toad likes frog)

GENERATIVE MODEL

- How about this other M_d:



$P(\text{STOP}|q_1) = 0.2$

the	0.2
a	0.1
frog	0.01
toad	0.01
said	0.03
likes	0.02
that	0.04
...	...

- We can calculate the probability of seen the sequence: “frog said that toad likes frog”.
  - P(frog said that toad likes frog): 0.0000000000001573
  - P(Today is Monday): 0.00001
  - P(The capital of Qatar is Doha): 0.00000012345

GENERAL WAY TO CALCULATE THE PROBABILITY OF A SEQUENCE

- Chain rule tell us that we need to calculate the following:

$P(w_1\ w_2\ w_3 \ldots w_N) = ?$

GENERAL WAY TO CALCULATE THE PROBABILITY OF A SEQUENCE

- Chain rule tell us that we need to calculate the following:

$$P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2|w_1)P(w_3|w_{1,}w_2)\ldots P(w_n|w_1 w_2 \ldots w_{n-1})$$

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Conditional dependences

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Conditional dependences

- How can we get rid of these conditional dependences?

GENERAL WAY TO CALCULATE THE PROBABILITY OF A SEQUENCE

- Chain rule tell us that we need to calculate the following:

$$P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2|w_1)P(w_3|w_{1,}w_2)\ldots P(w_n|w_1w_2\ldots w_{n-1})$$

Conditional dependences

- How can we get rid of these conditional dependences?
  - Again: assuming some degree of **independence** for terms in a text

Example: $P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2)P(w_3)\ldots P(w_n)$

PROBABILITY OF GENERATING A TEXT

- Unigram Language model: **No Conditional dependences at all**

$$P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2)P(w_3)\ldots P(w_n)$$

- Bigram Langauge model: **Dependence restrict the last term**

$$P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2|w_1)P(w_3|w_2)\ldots P(w_n|w_{n-1})$$

- Trigram Language model: **Dependence restrict the last two terms**

$$P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2|w_1)P(w_3|w_2 w_1)\ldots P(w_n|w_{n-1} w_{n-2})$$

- N-gram Language model: **Dependence restrict the last n-1 terms**

$$P(w_1\ w_2\ w_3 \ldots w_N) = P(w_1)P(w_2|w_1)P(w_3|w_2 w_1)\ldots P(w_n|w_{n-1} w_{n-2 \ldots} w_{n-N-1})$$

Which one to use?

IN INFORMATION RETRIEVAL…

- Most of the time we use the Unigram Language Model. Why?

  Simple enough and powerful enough for this task

IN INFORMATION RETRIEVAL…

- Most of the time we use the Unigram Language Model. Why?

LM ϕ_1

qatar	0.01
location	0.002
south	0.003
arab	0.0009
…	
nutrition	0.00002
food	0.00000001

LM ϕ_2

qatar	0.00000003
location	0.0001
south	0.00005
arab	0.003
…	
nutrition	0.001
food	0.01

IN INFORMATION RETRIEVAL…

- Most of the time we use the Unigram Language Model. Why?

LM ϕ_1

qatar 0.01
location 0.002
south 0.003
arab 0.0009
…
nutrition 0.00002
food 0.00000001

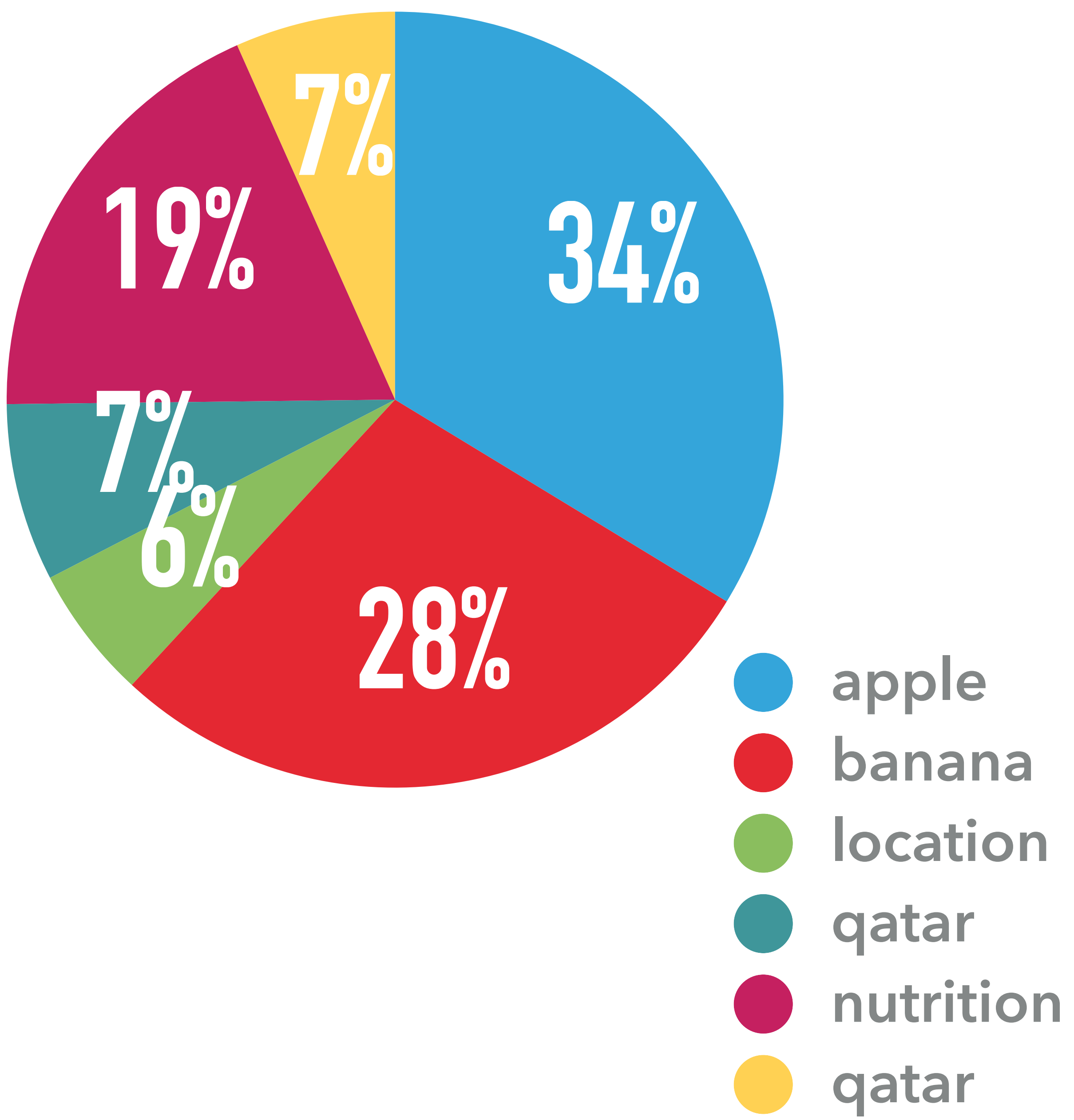
Word distribution for a document about the location of qatar

LM ϕ_2

qatar 0.00000003
location 0.0001
south 0.00005
arab 0.003
…
nutrition 0.001
food 0.01

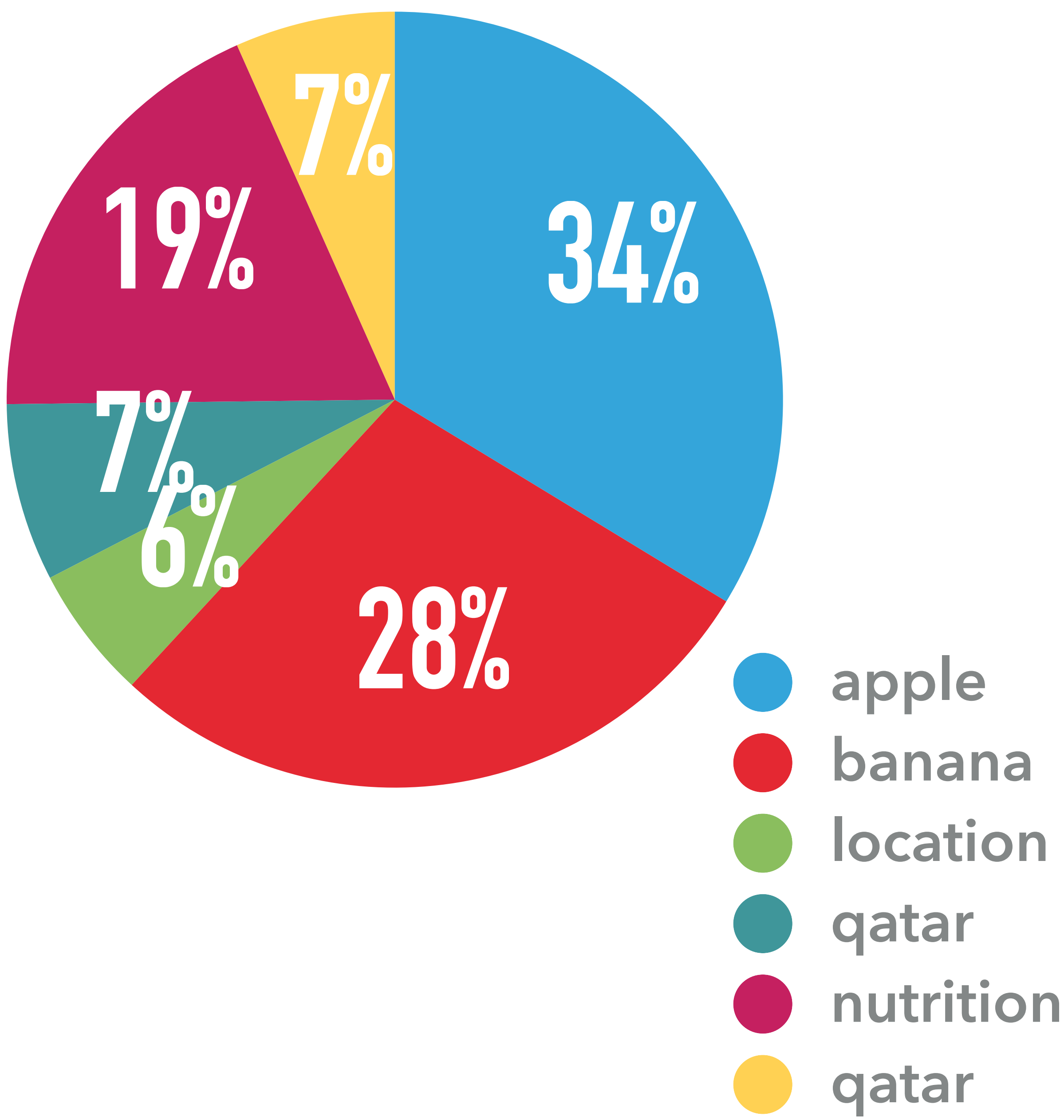
Word distribution for a document about health food

GENERATING TEXT IN UNIGRAM LM



- Throw a dice…

GENERATING TEXT IN UNIGRAM LM



- Throw a dice…
  - Generates word W_1
- Throw another dice…
  - Generates word W_2
- Throw a dice again…
  - Generates word W_3

FROM TEXT TO PROBABILITIES…

Qatar is a sovereign country located in Western Asia, occupying the small Qatar Peninsula on the northeastern coast of the Arabian Peninsula. Its sole land border is with Saudi Arabia to the south, with the rest of its territory surrounded by the Persian Gulf. A strait in the Persian Gulf separates Qatar from the nearby island country of Bahrain, as well as sharing maritime borders with the United Arab Emirates and Iran.

- P("qatar") = 3/79
- P(".") = 3/79
- P("gulf") = 2/79
- P("arab") = 3/79
- P("asia") = 1/79
- P("land") = 1/79
- P("persian") = 2/79
- P("peninsula") = 2/79

FROM PROBABILITIES TO TEXT…

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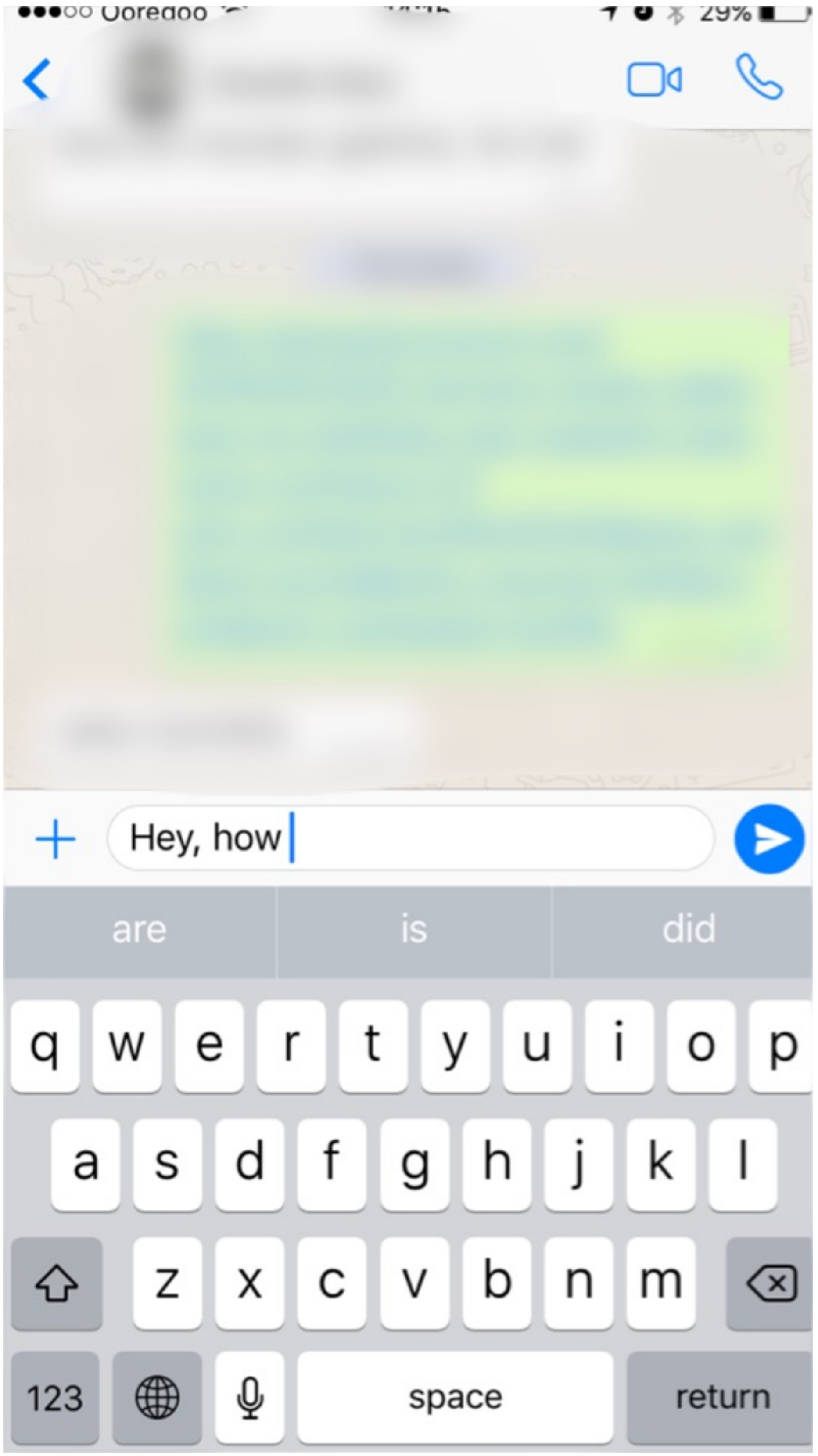
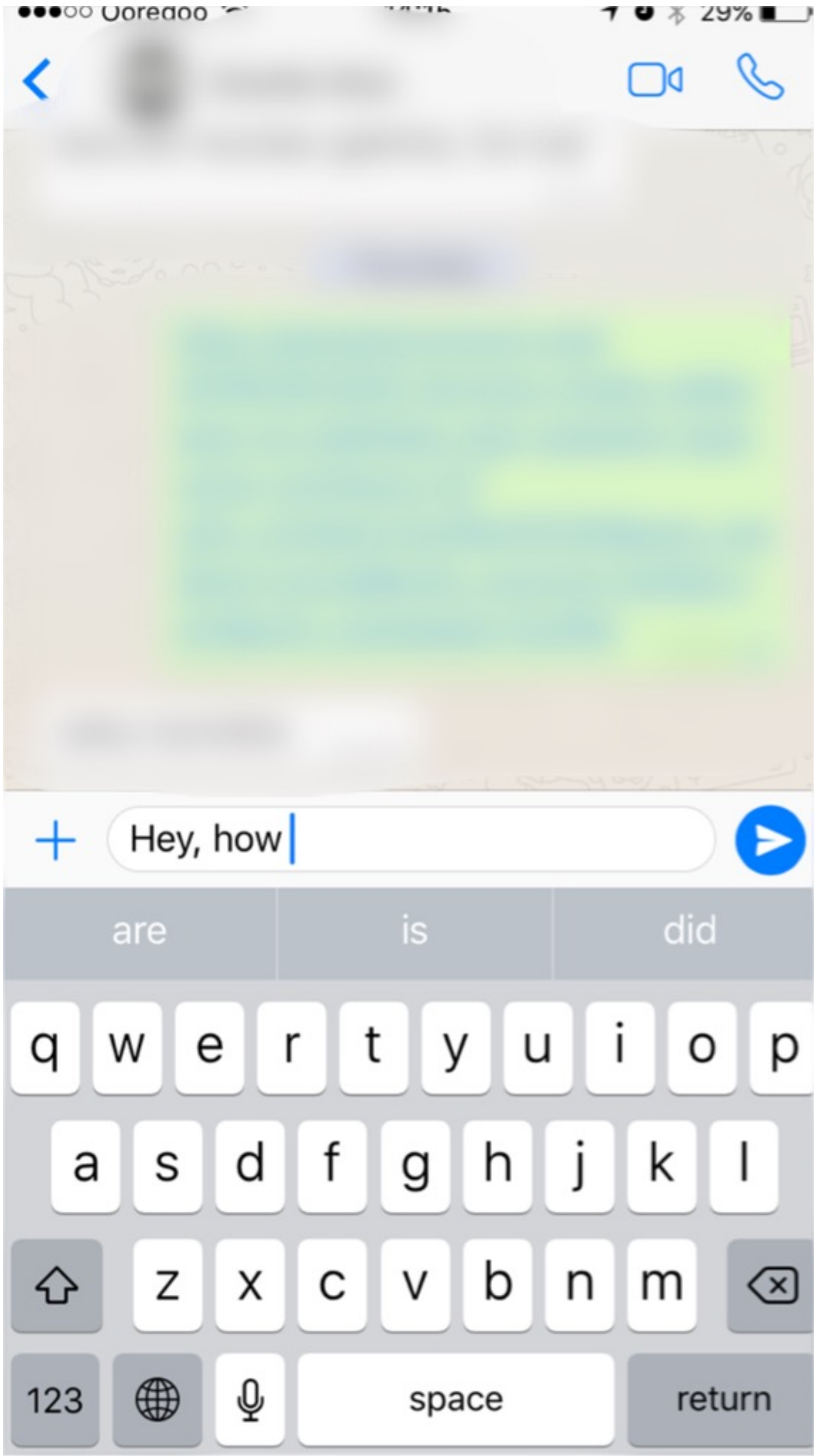
- P("persian") = 2/79
- P("peninsula") = 2/79

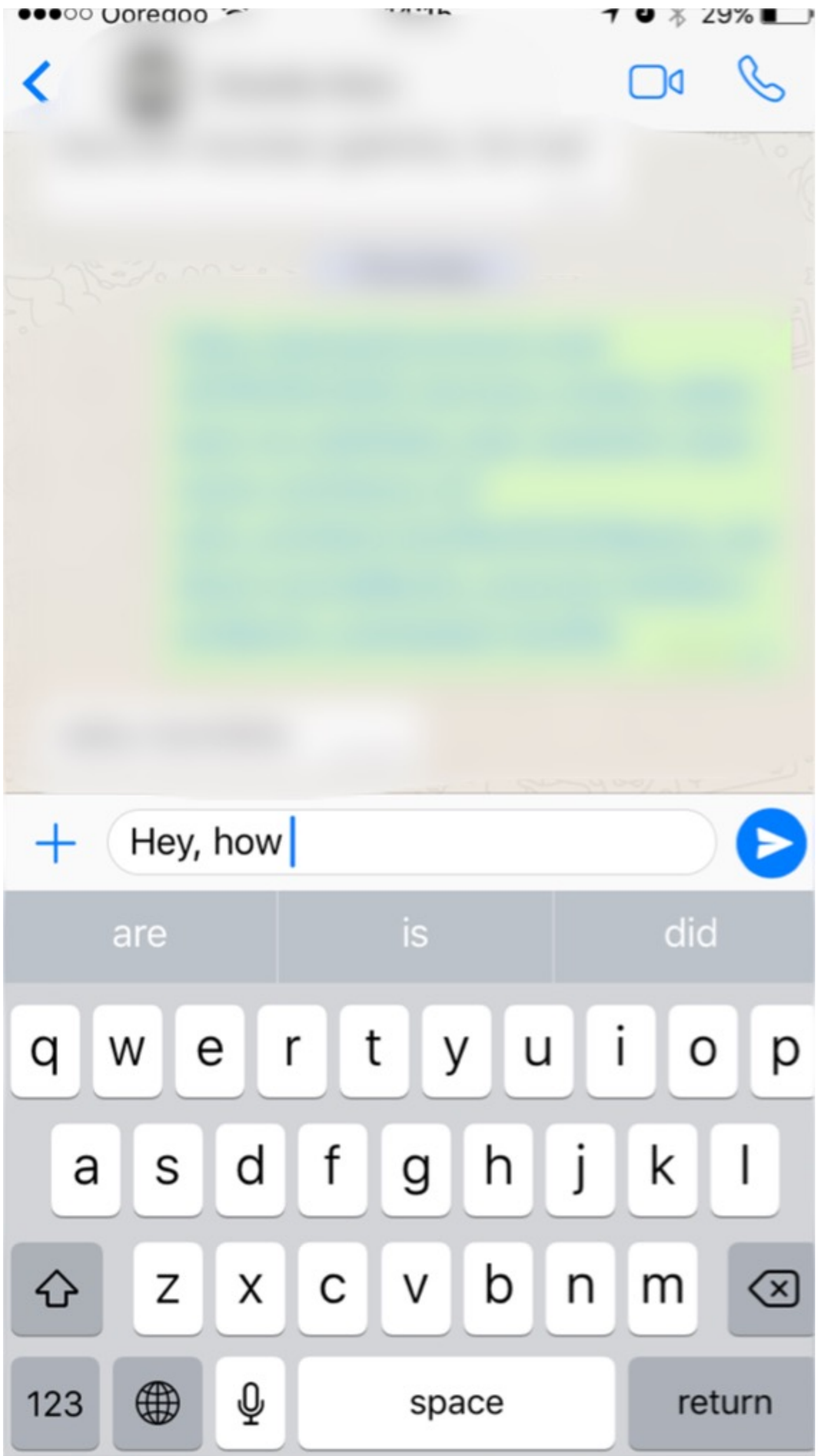
Gulf United as surrounded . well Qatar is Persian a of nearby Peninsula rest coast sovereign Arabian country south located in Western Asia, occupying Persian the small Qatar on the northeastern of the Peninsula . Its sole land border is Emirates with Arabia to the . Saudi , with the of its territory by the A strait in the Gulf Qatar from the island country , as separates Iran maritime Bahrain borders with the Arab sharing and



- How can we generate these suggestions?



- How can we generate these suggestions?
- E.g. Top 3 term T that maximize:
  - P(T | “Hey, how”)
  - P(“are” | “Hey, how”) > P (“house” | “Hey, how”)
  - P(“are” | “Hey, how”) > P (“do” | “Hey, how”)



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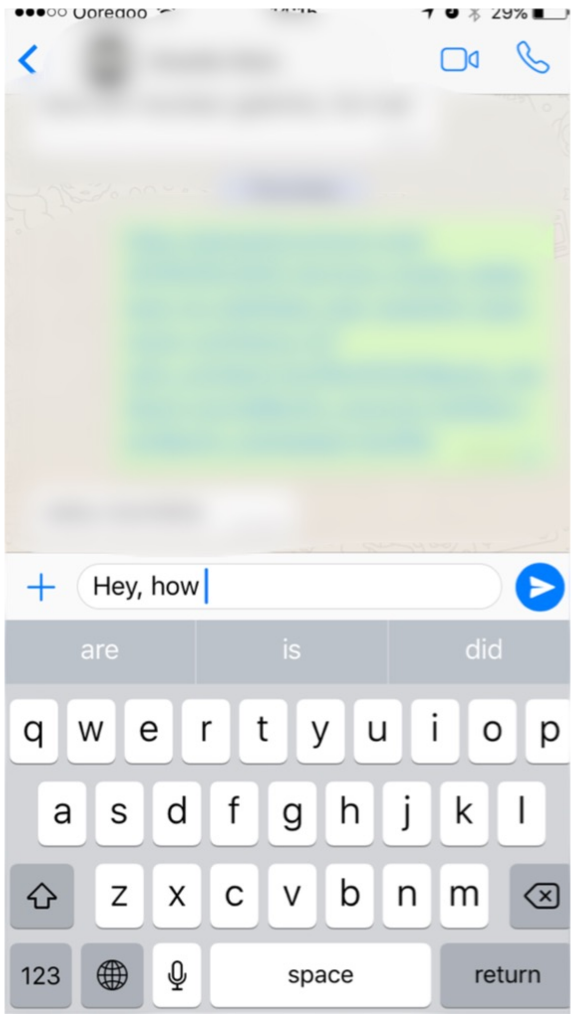
  - P("are" | "Hey, how") > P ("do" | "Hey, how")

Unigrams are not enough for this other task…

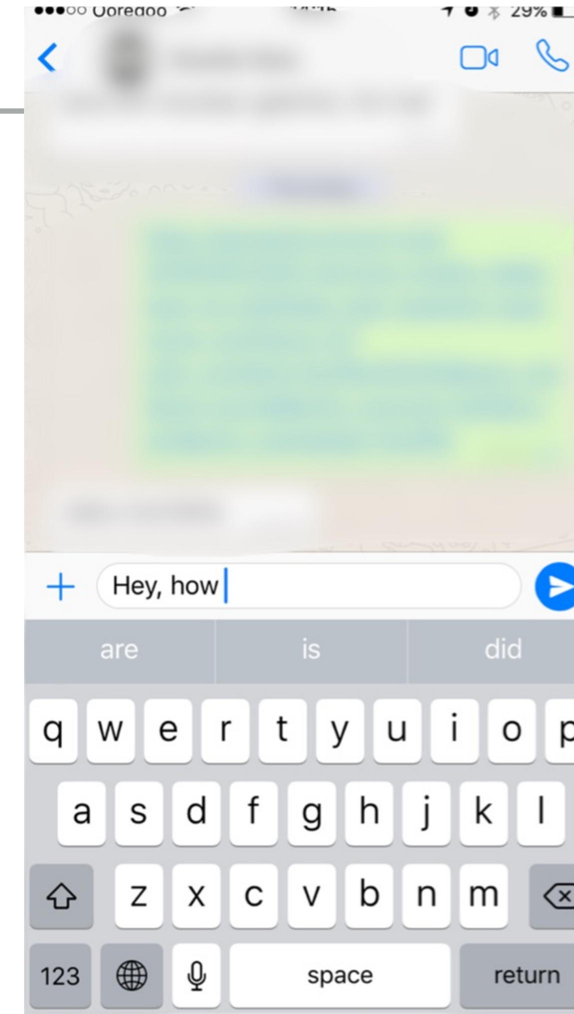
GENERATING TEXT IN BIGRAM LM

- P("qatar" | <bos>) = 0.00001
- P("you" | <bos>) = 0.01



- Throw a dice for the first word:
  - Generates word W_1

GENERATING TEXT IN BIGRAM LM

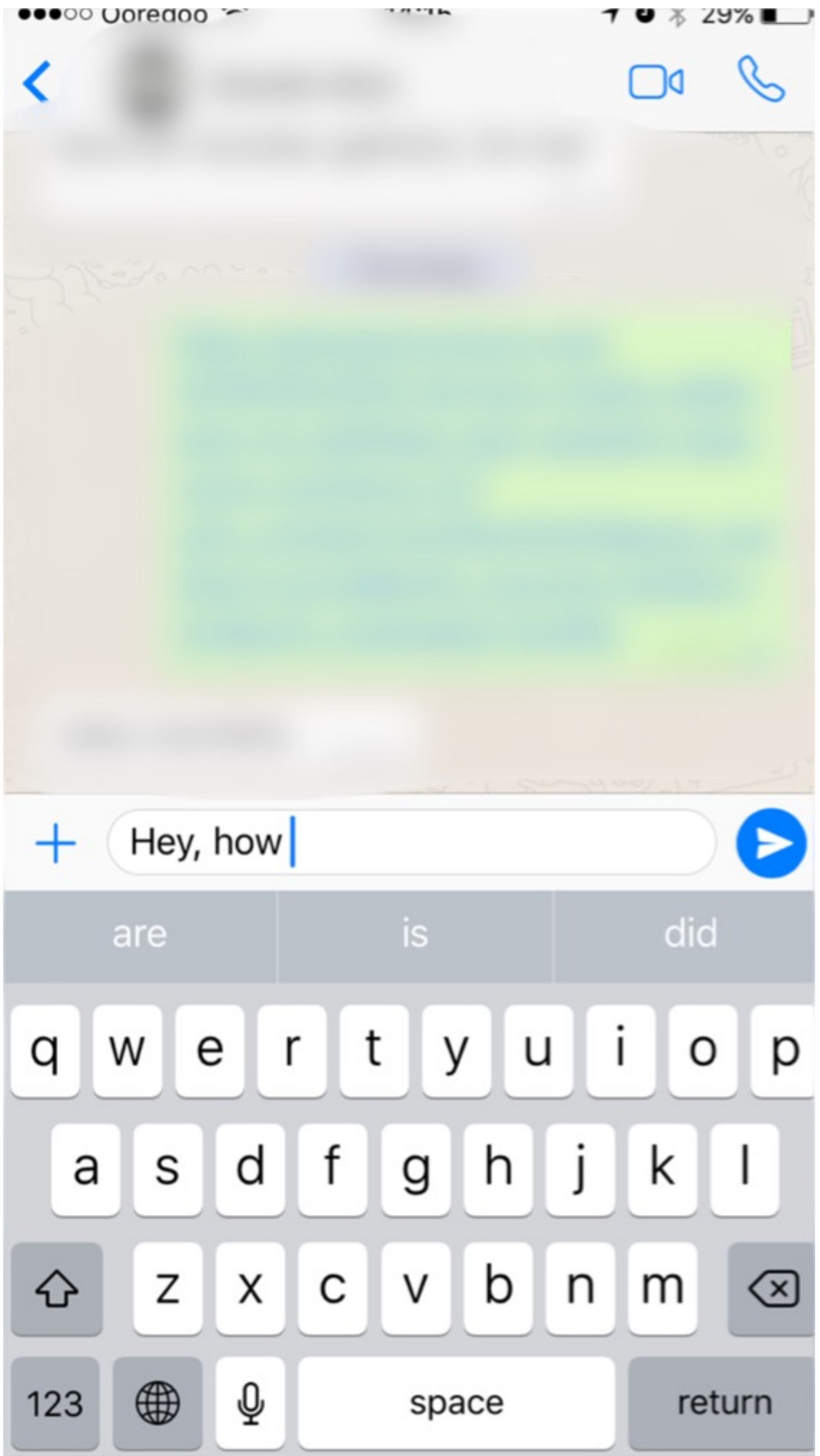


- P(“qatar” | <bos>) = 0.00001
- P(“you” | <bos>) = 0.01

…

- P(“are” | “you”) = 0.02
- P(“is” | “you”) = 0.00001
- P(“were” | “you”) = 0.01
- P(“am” | “you”) = 0.0001
- P(“think” | “you”) = 0.003

- Given the first word, throw a dice for the second word:
  - Generates word W_2 given W_1



- E.g. Top 3 term T that maximize:
  - P(T | “Hey, how”)
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  - P(“are” | “Hey, how”) > P (“do” | “Hey, how”)

Is the max a good function to be implemented here? Why?

FUNNY COMPARISON

GENERATED FROM LANGUAGE MODELS OF THE NEW YORK TIMES

- Unigram:

Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a q acquire to six executives.

- Bigram:

Last December through the way to preserve the Hudson corporation N.B.E.C. Taylor would seem to complete the major central planners one point five percent of U.S.E. has already told M.X. corporation of living on information such as more frequently fishing to keep her

- Trigram:

They also point to ninety nine point six billon dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions.

https://pdos.csail.mit.edu/archive/scigen/

HOW CAN WE START GENERATING TEXT?

Qatar is a sovereign country located in Western Asia, occupying the small Qatar Peninsula on the northeastern coast of the Arabian Peninsula. Its sole land border is with Saudi Arabia to the south, with the rest of its territory surrounded by the Persian Gulf. A strait in the Persian Gulf separates Qatar from the nearby island country of Bahrain, as well as sharing maritime borders with the United Arab Emirates and Iran.

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- P("persian") = 2/79
- P("peninsula") = 2/79
- P("brazil") = 0/79
- P("food") = 0/79
- P("continent") = 0/79
- P("house") = 0/79

HOW CAN WE START GENERATING TEXT?

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MAXIMUM LIKELIHOOD ESTIMATION

- P("qatar") = 3/79
- P("asia") = 1/79
- P("brazil") = 0/79
- P(".") = 3/79
- P("land") = 1/79
- P("food") = 0/79
- P("gulf") = 2/79
- P("persian") = 2/79
- P("continent") = 0/79
- P("arab") = 3/79
- P("peninsula") = 2/79
- P("house") = 0/79

Bag of words again - assume independence between any two tokens

LANGUAGE MODELS FOR IR

Documents

LM ϕ_1

qatar 0.01
location 0.002
south 0.003
arab 0.0009
...
nutrition 0.00002
food 0.00000001

LM ϕ_2

qatar 0.00000003
location 0.0001
south 0.00005
arab 0.003
...
nutrition 0.001
food 0.01

Query

"capital arabic countries"

LANGUAGE MODELS FOR IR

Documents

LM ϕ_1

qatar 0.01
location 0.002
south 0.003
arab 0.0009
...
nutrition 0.00002
food 0.00000001

LM ϕ_2

qatar 0.00000003
location 0.0001
south 0.00005
arab 0.003
...
nutrition 0.001
food 0.01

Query

"capital arabic countries"

Retrieval question:

WHAT IS THE MOST LIKELY DOCUMENT THAT GENERATED THIS QUERY?

LANGUAGE MODELS FOR IR

Documents

LM ϕ_1

qatar 0.01
location 0.002
south 0.003
arab 0.0009
...
nutrition 0.00002
food 0.00000001

LM ϕ_2

qatar 0.00000003
location 0.0001
south 0.00005
arab 0.003
...
nutrition 0.001
food 0.01

Query

"capital arabic countries"

Retrieval question:

WHAT IS THE MOST LIKELY DOCUMENT THAT GENERATED THIS QUERY?

$$P(Q|\phi_1) > P(Q|\phi_2)$$

or

$$P(Q|\phi_2) > P(Q|\phi_1)$$

THEORETIC REASONING BASED ON PRP

$$P(d|q)$$

THEORETIC REASONING BASED ON PRP

USING BAYES' THEOREM AGAIN…

$$P(d|q) = \frac{P(q|d)P(d)}{P(q)}$$

THEORETIC REASONING BASED ON PRP

It can be a constant…
or it can be a proxy for
document popularity,
document credibility,
document readability…

$$P(d|q) = \frac{P(q|d)\boxed{P(d)}}{\boxed{P(q)}}$$

It is a constant for every
document in the collection.

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Let's assume a document d can be represented by its language model **ϕ**

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document in the collection.

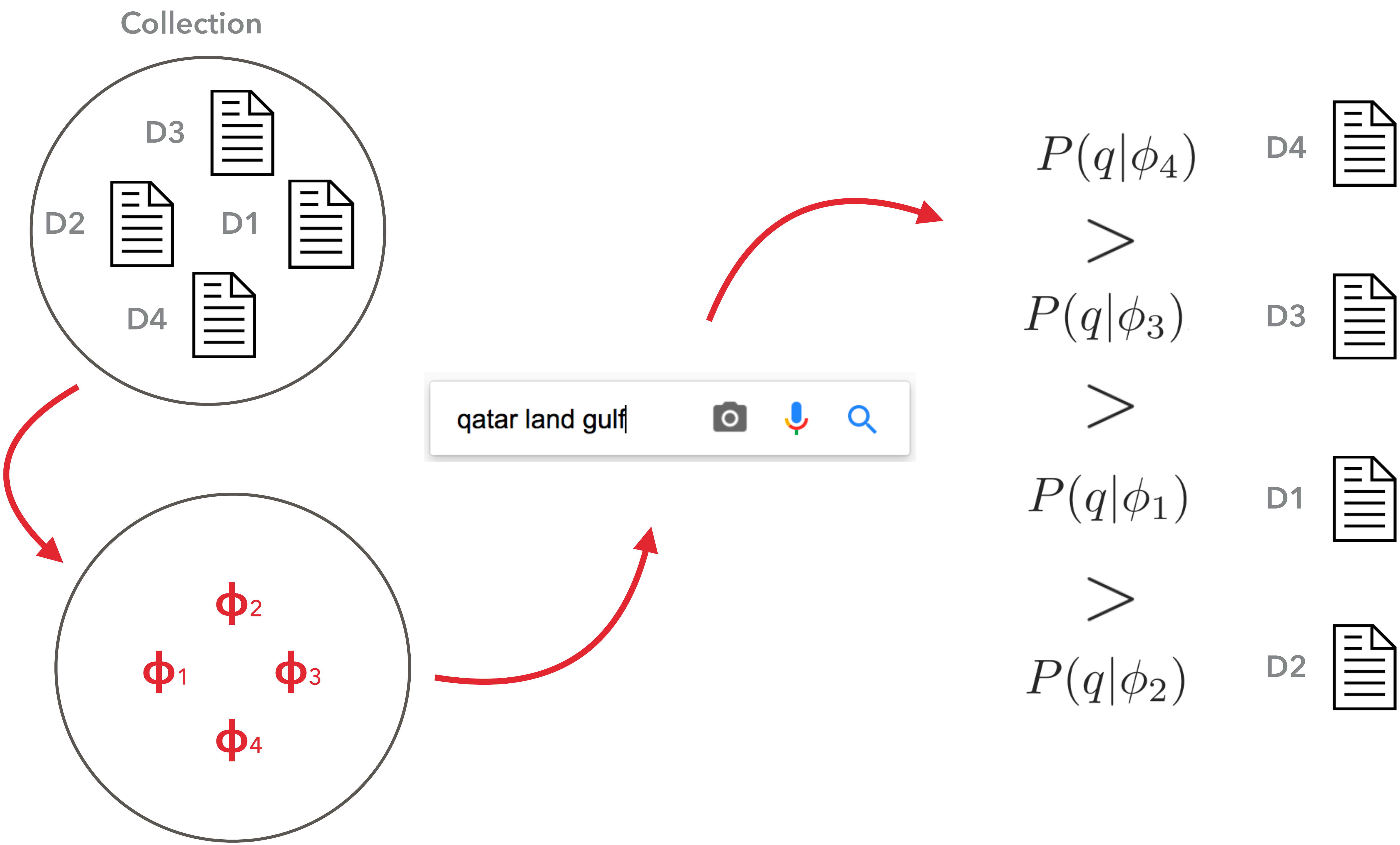
Let's assume a document <u>d</u> can be represented by its language model **ϕ**

$$P(q|\phi)$$

<u>**That is all that we need to calculate!**</u>

THEORETIC REASONING BASED ON PRP

$$P(q|\phi)$$



LM WITH MAXIMUM LIKELIHOOD ESTIMATION $P(q|\phi)$

- Document D transformed in LM ϕ:

P("qatar") = 3/79	P("asia") = 1/79	P("brazil") = 0/79
P(".") = 3/79	P("land") = 1/79	P("food") = 0/79
P("gulf") = 2/79	P("persian") = 2/79	P("continent") = 0/79
P("arab") = 3/79	P("peninsula") = 2/79	P("house") = 0/79

- Query: "qatar land gulf"
- P("qatar land gulf" | ϕ) = 3/79 * 1/79 * 2/79 = 1.21e-05

LM WITH MAXIMUM LIKELIHOOD ESTIMATION

$$P(q|\phi)$$

- Document D transformed in LM ϕ:

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- Query: "qatar land gulf"
- P("qatar land gulf" | ϕ) = 3/79 * 1/79 * 2/79 = 1.21e-05

Rembember: UNIGRAM model independence between any two tokens

$$P(q|d) = \prod_{w} P(w|)$$

LM WITH MAXIMUM LIKELIHOOD ESTIMATION

- Actually, we DO NOT calculate the multiplication of the probabilities…

LM WITH MAXIMUM LIKELIHOOD ESTIMATION

- Actually, we DO NOT calculate the multiplication of the probabilities…

$$P(q|d) = \prod_{w} P(w|) = \sum_{w} \log P(w|\phi)$$

$$P(w|d) = \frac{c(w,d)}{|d|}$$

PROBLEM…

- Document D transformed in LM ϕ:

P("qatar") = 3/79	P("asia") = 1/79	P("brazil") = 0/79
P(".") = 3/79	P("land") = 1/79	P("food") = 0/79
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P("arab") = 3/79	P("peninsula") = 2/79	P("house") = 0/79

- Query: "qatar land continent"

PROBLEM…

- Document D transformed in LM ϕ:

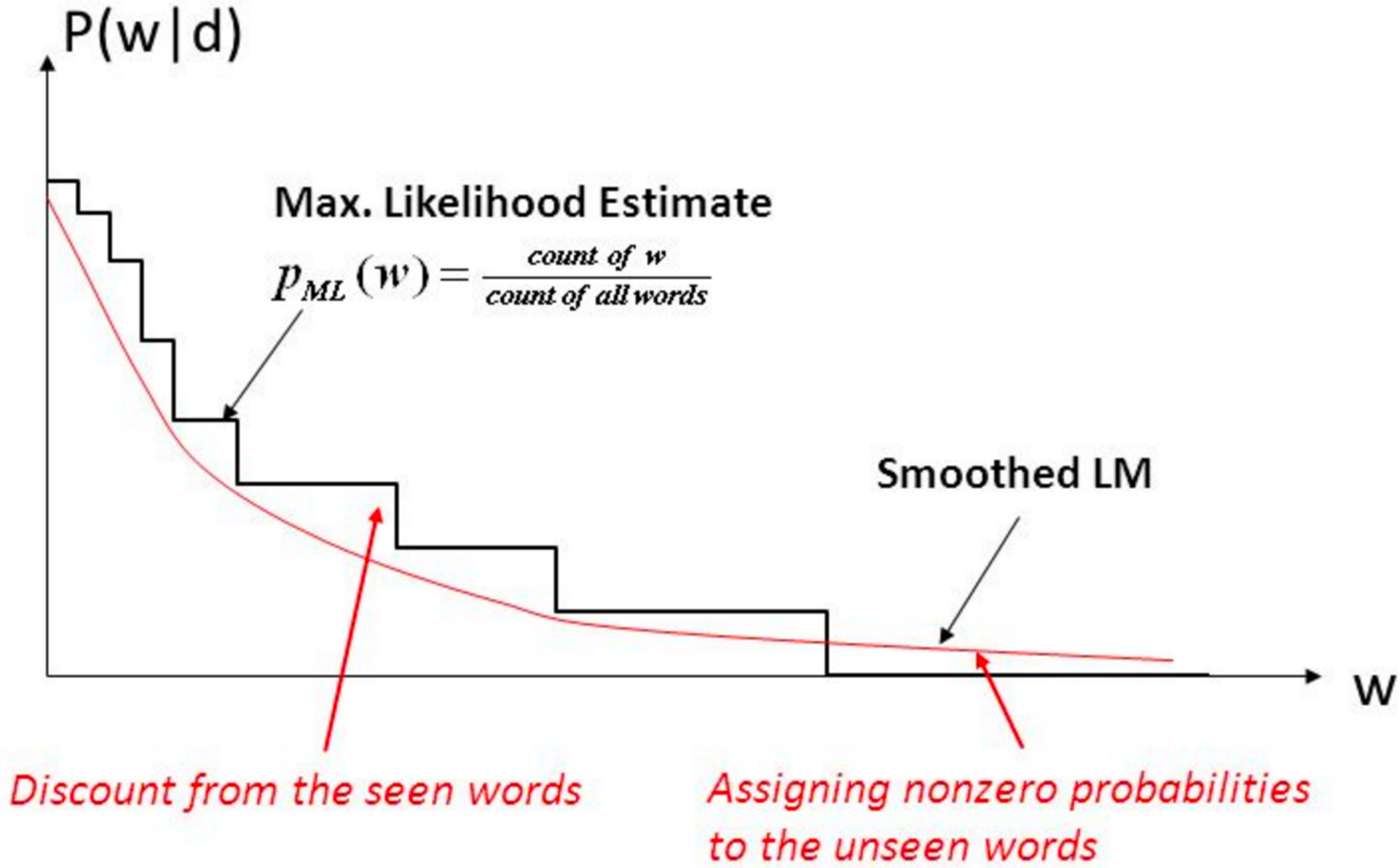
P("qatar") = 3/79	P("asia") = 1/79	P("brazil") = 0/79
P(".") = 3/79	P("land") = 1/79	P("food") = 0/79
P("gulf") = 2/79	P("persian") = 2/79	P("continent") = 0/79
P("arab") = 3/79	P("peninsula") = 2/79	P("house") = 0/79

- Query: "qatar land continent"
- P("qatar land <u>continent</u>" | ϕ) = 3/79 * 1/79 * 0/79 = 0

DOES IT MEAN THAT A DOCUMENT WITHOUT ANY QUERY KEYWORD IS NOT RELEVANT?

IDEA OF ANY SMOOTHING METHOD

- We want to give non-zero probabilities for unseen keywords
- We discount a very tiny bit of the probability of each seen word and re-allocate this tiny bit to unseen words
- In a smoothed LM: $\forall w \; P(w \mid \phi) > 0.0$


P(w|d)
Max. Likelihood Estimate
$p_{ML}(w) = \frac{count\ of\ w}{count\ of\ all\ words}$
Smoothed LM
w
Discount from the seen words
Assigning nonzero probabilities
to the unseen words

SMOOTHING METHODS

- Method 1: Additive Smoothing / Laplace smoothing

$$P(w|d) = \frac{c(w,d) + \alpha}{|d| + \alpha|V|}$$

- Often alpha is set to 1:

$$P(w|d) = \frac{c(w,d) + 1}{|d| + |V|}$$

SMOOTHING METHODS

- Method 2: Linear Interpolation, Jelinek-Mecer

$$P(w|d) = (1-\lambda)\frac{c(w,d)}{|d|} + (1-\lambda)p(w|Collection)$$

- Often lambda takes any value between 0 and 1

PROBABILITIES CAN BE CALCULATED FROM ANY COLLECTION
(YOUR OWN COLLECTION? WIKIPEDIA? WHOLE WEB?)

SMOOTHING METHODS

- Method 3: Dirichlet Prior / Bayesian

$$P(w|d) = \frac{c(w,d) + \mu p(w|Collection)}{|d| + \mu}$$

- It is kind of a mix from previous methods

SUMMARY - USING LM FOR IR

- Choose your favorite smoothing method and parameter
- Calculate smoothed $P(Q \mid D)$ for each D in collection
- Rank documents with respect to their probabilities
- Return top K documents (e.g., K = 10) to the user
- Statistical natural language processing motivation

WHAT DID WE SEE? WHAT SHOULD YOU KNOW?

- Notes on floating representation in a computer
- Language Model
- Smoothing Methods

TODAY'S LECTURE IN THE STANFORD IR BOOK

- Chapter 12: Language models for information retrieval

HOMEWORK 1

- Comments about it from students
- Comments about it from me

HOMEWORK 2

- Explanation