

# First Glance on Pattern-based Language Modeling

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# Presentation outline

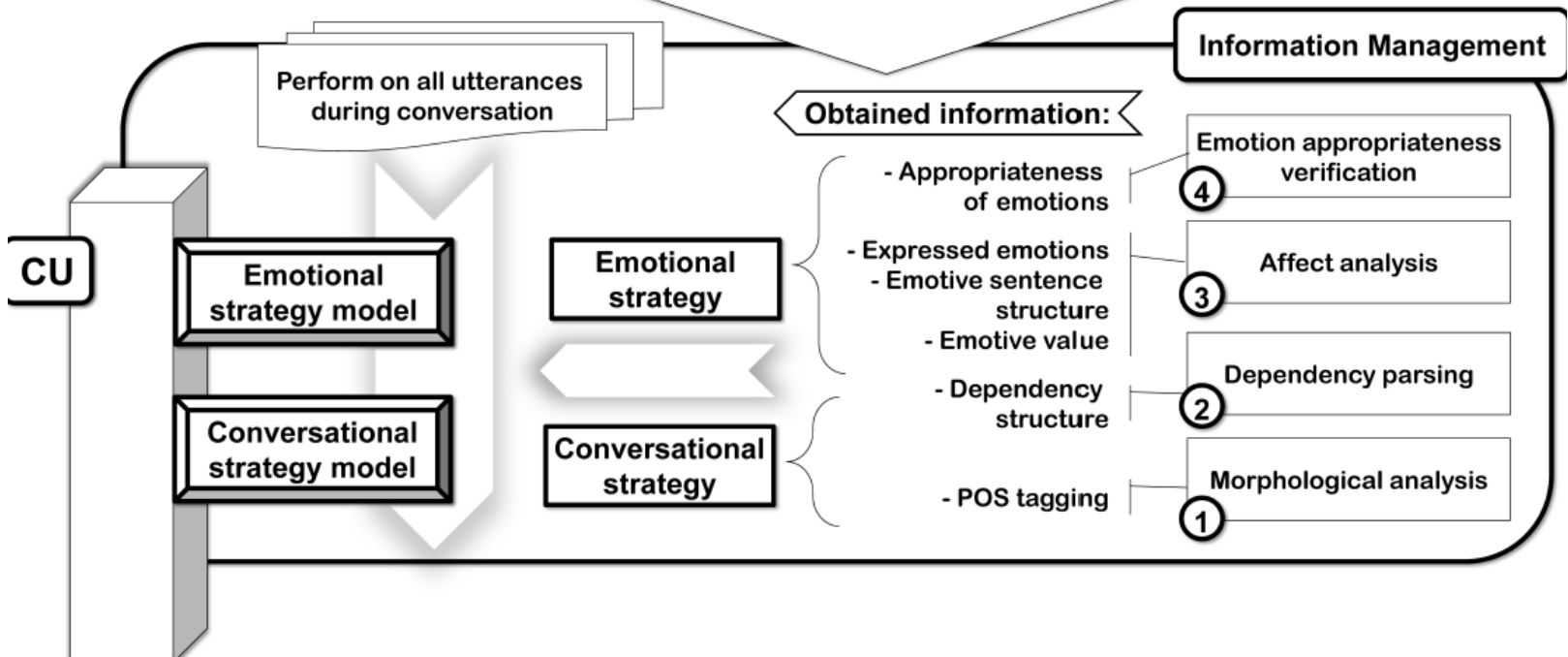
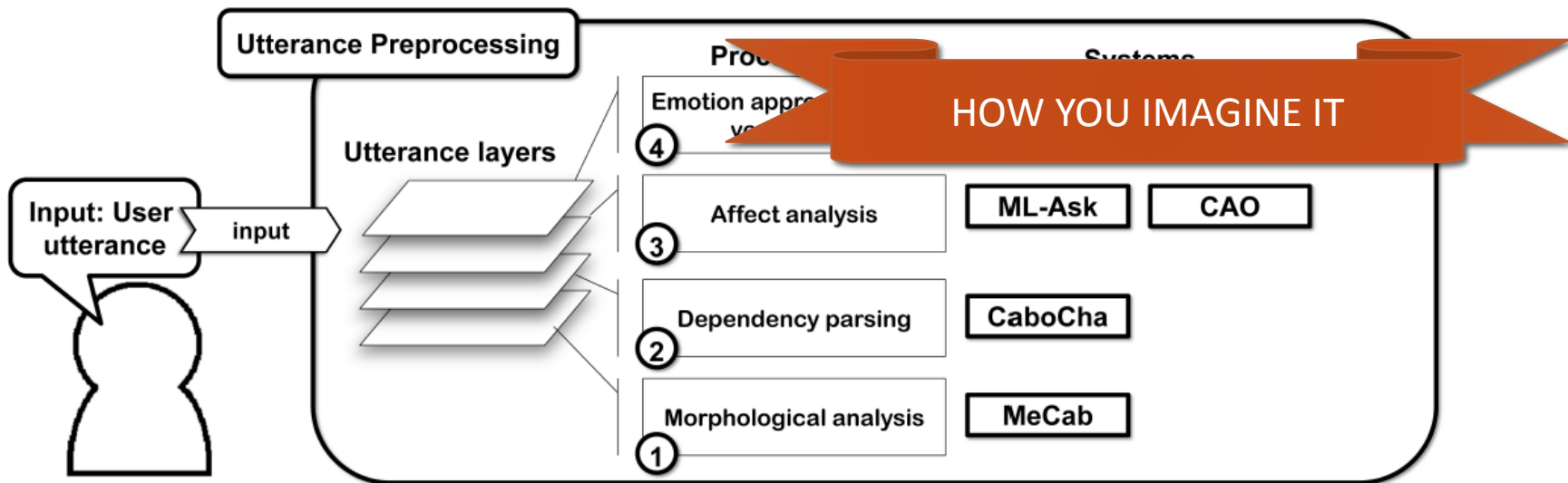
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1. Introduction
2. Language Models
3. Language Combinatorics
4. Applications
5. Conclusions and Future work

# Introduction

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Language modelling



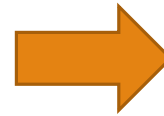
# Introduction

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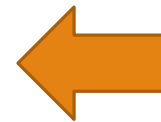
## Language modelling

John likes to watch movies. Mary likes movies too.

John also likes to watch football games.



```
{  
  "John": 1,  
  "likes": 2,  
  "to": 3,  
  "watch": 4,  
  "movies": 5,  
  "also": 6,  
  "football": 7,  
  "games": 8,  
  "Mary": 9,  
  "too": 10  
}
```



```
[1, 2, 1, 1, 2, 0, 0, 0, 1, 1]  
[1, 1, 1, 1, 0, 1, 1, 1, 0, 0]
```

# Introduction

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## Language modelling

- Statistical representation of a piece of language data

# Language Models

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1. Bag-of-words
2. N-gram
3. Skip-gram

# Language Models

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1. Bag-of-words
2. N-gram
3. Skip-gram

Unordered set of words

The dog bit the man = The man bit the dog

- No grammar
- No word order
- Just a bag of words...



# Language Models

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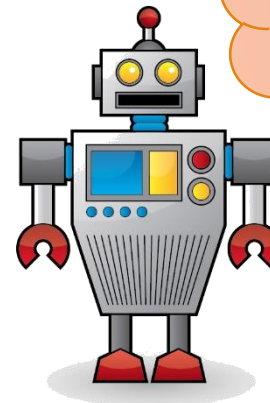
1. Bag-of-words
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Unordered set of words

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LEARNING



Harris, Zellig. 1954. Distributional Structure. Word, 10 (2/3), pp. 146-162.

# Language Models

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2. N-gram
3. Skip-gram

Unordered set of words

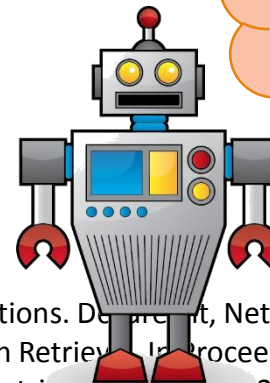
The dog bit the man = The man bit the dog

- No grammar
- No word order
- Just a bag of words...

Modifications:

- Positional Language Model
- Bag-of-concept

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- Harris, Zellig. 1954. Distributional Structure. *Word*, 10 (2/3), pp. 146-162.
- E. Cambria and A. Hussain. 2012. *Sentic Computing: Techniques, Tools, and Applications*. Dordrecht, Netherlands: Springer.
- Yuanhua Lv and ChengXiang Zhai. 2009. Positional Language Models for Information Retrieval. In *Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval*, pp. 299-306.

# Language Models

---

1. Bag-of-words
2. N-gram
3. Skip-gram

Sentence = set of n-long ordered sub-sequences of words.

The dog bit the man

2grams:

the dog | dog bit | bit the | the man

3grams:

the dog bit | dog bit the | bit the man

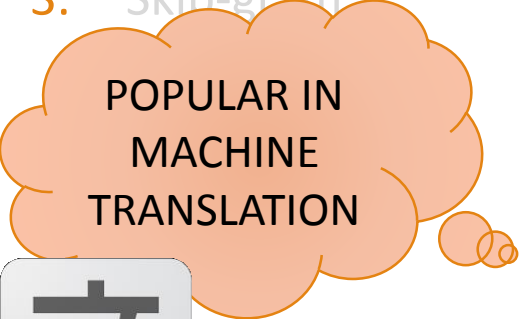
4grams:

the dog bit the | dog bit the man

# Language Models

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1. Bag-of-words
2. N-gram
3. Skin-gram



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TRANSLATION



Sentence = set of n-long ordered sub-sequences of words.

The dog bit the man

2grams:

the dog | dog bit | bit the | the man

3grams:

the dog bit | dog bit the | bit the man

4grams:

the dog bit the | dog bit the man

# Language Models

---

1. Bag-of-words
2. N-gram
3. Skip-gram

Sentence = set of n-long ordered sub-sequences of words.

(1) John went to school today.

John went



went to



John \* school



# Problem definition

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ああ、今日はなんて気持ちいい日なんだ！  
(Oh, what a pleasant day today, isn't it?)

This sentence contains the pattern:

ああ \* なんて \* なんだ！ (Oh, what a \* isn't it?)

1. This pattern cannot be discovered with n-gram approach.
2. This pattern cannot be discovered if one doesn't know what to look for.

**Need to find a way to extract such frequent sophisticated patterns from corpora.**

\*) pattern = something that frequently appears in a corpus (more than once).

# Language Models

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1. Bag-of-words
2. N-gram
3. Skip-gram

# Language Models

---

1. Bag-of-words
2. N-gram
3. Skip-gram

Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

John went	👍
went to	👍
John * to	👍

3gram: John went to  
1skip2gram: John \_ to





# Language Models

1. Bag-of-words
2. N-gram
3. Skip-gram

Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

John went           👍  
went to              👍  
John \* to            👍

To do this  
you need to...

3gram:       John went to  
1skip2gram: John \_ to



# Language Models

Skip-gram model  
with modified  
Kneser-Ney  
Smoothing

$$\partial_1 w_{i-n+1}^i = w_{i-n+2}^i$$

$$\hat{P}_{\text{MKN}}(w_i | w_{i-n+2}^{i-1}) = \hat{P}_{\text{MKN}}(w_i | \partial_1 w_{i-n+1}^{i-1})$$

$$\hat{P}_{\text{MKN}}(w_i | (w_{i-n+1}^{i-1})) =$$

$$\frac{\max\{N_{1+}(\bullet w_{i-n+1}^i) - D(c(w_{i-n+1}^i)), 0\}}{N_{1+}(\bullet w_{i-n+1}^{i-1} \bullet)}$$

$$+ \gamma_{mid}(w_{i-n+1}^{i-1}) \hat{P}_{\text{MKN}}(w_i | w_{i-n+2}^{i-1}) \dots$$

# Language Models

1. Bag-of-words
2. N-gram
3. Skip-gram

And still don't get the whole picture.

Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

(2) John went to this awful place many people tend to generously call school today.

John went



went to



John \* to



John \* school



John \* to \* today



# Language Models

1. Bag-of-words
2. N-gram
3. Skip-gram

Skip-grams cannot help extracting such patterns because...


Sentence = some words within an n-gram can be skipped over

(1) John went to school today.


(2) John went to this awful place many people tend to generously call school today.

John went 

went to 

John \* to 

John \* school 

John \* to \* today 

# Language Models






1. Bag-of-words
2. N-gram
3. Skip-gram

1. The “skip” can appear only in one place.

Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

(2) John went to this awful place many people tend to generously call school today.

John went	
went to	
John * to	
John * school	
John * to * today	

# Language Models






1. Bag-of-words
2. N-gram
3. Skip-gram

1. The “skip” can appear only in one place.
2. The same number of skips needs to be retained for each gap.

Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

(2) John went to this awful place many people tend to generously call school today.

John went	
went to	
John * to	
John * school	
John * to * today	

# Language Models

1. Bag-of-words
2. N-gram
3. Skip-gram

1. The “skip” can appear only in one place.
2. The same number of skips needs to be retained for each gap.
3. Full control of the skip-length.

Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

w s{1} w s{1} w

(2) John went to this awful place many people tend to generously call school today.

w s{1} w s{10} w

John went



went to



John \* to



John \* school



John \* to \* today



NOT SO  
POPULAR



# Language Models

1. Bag-of-words
2. N-gram
3. Skip-gram

1. The “skip” can appear only in one place.
2. The same number of skips needs to be retained for each gap.
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Sentence = some words within an n-gram can be skipped over

(1) John went to school today.

$w s\{1\} w s\{1\} w$

(2) John went to this awful place many people tend to generously call school today.

$w s\{1\} w s\{10\} w$

John went



went to



John \* to



John \* school



**John \* to \* today**





# Language Models

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1. Bag-of-words
2. N-gram
3. Skip-gram

Solution &  
simplification:

$$\binom{n}{k}$$

# Language combinatorics

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## SPEC – Sentence Pattern Extraction arChitecture

**Sentence pattern = ordered non-repeated combinations of sentence elements.**

For  $1 \leq k \leq n$ , there is  $\binom{n}{k} = \frac{n!}{k!(n-k)!}$  all possible  $k$ -long patterns, and

$$\sum_{k=1}^n \binom{n}{k} = \frac{n!}{1!(n-1)!} + \frac{n!}{2!(n-2)!} + \dots + \frac{n!}{n!(n-n)!} = 2^n - 1$$

# Language combinatorics

## SPEC – Sentence Pattern Extraction arChitecture

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Extract patterns from all sentences and calculate occurrence.

# Language combinatorics

## SPEC – Sentence Pattern Extraction arChitecture

**Sentence pattern = ordered non-repeated combinations of sentence elements.**

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And then  
classify/  
compare  
emotive  
sentences  
with non-  
emotive

Normalized pattern weight

$$w_j = \left( \frac{O_{pos}}{O_{pos} + O_{neg}} - 0.5 \right) * 2$$

Score for one sentence

$$score = \sum w_j, (1 \geq w_j \geq -1)$$

# Language combinatorics

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# Language combinatorics

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1. Bag-of-words
2. N-gram
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4. Language combinatorics

Sentence = some words within an n-gram can be skipped over

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John went 

went to 

John \* to 

John \* school 

John \* to \* today 

# Applications

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# Applications

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1. Emotive / non-emotive [50 emotive and 41 non-emotive]
2. Future reference sentences [130 + 130 sentences]
3. Cyberbullying [1500 + 1500 sen.]
4. Conversations (male / female, social distance close / far, students / adults, ...) [4000 sen., 6000 sen.]
5. Detection of depressive tendencies [10,000 sen.]
6. Determining specific emotions (joy, anger, fear, ...) [~100 sen. x 10 classes (multiclass)]

- Michal Ptaszynski, Fumito Masui, Rafal Rzepka, Kenji Araki. 2014. Automatic Extraction of Emotive and Non-emotive Sentence Patterns, In Proceedings of The Twentieth Annual Meeting of The Association for Natural Language Processing (NLP2014), pp. 868-871, Sapporo, Japan, March 17-21.
- Michal Ptaszynski, Fumito Masui, Rafal Rzepka, Kenji Araki. 2014. Emotive or Non-emotive: That is The Question, In Proceedings of 5th Workshop on Computational Approaches to Subjectivity, Sentiment & Social Media Analysis (WASSA 2014), pp. 59-65, held in conjunction with The 52nd Annual Meeting of the Association for Computational Linguistics (ACL 2014), Baltimore, USA, June 22-27.
- Michal Ptaszynski, Fumito Masui, Rafal Rzepka, Kenji Araki. 2014. Detecting emotive sentences with pattern-based language modelling. In Proceedings of 18th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES2014), Gdynia, Poland (to appear).
- Michal Ptaszynski, Dai Hasegawa, Fumito Masui, Hiroshi Sakuta, Eijiro Adachi. 2014. How Differently Do We Talk? A Study of Sentence Patterns in Groups of Different Age, Gender and Social Status. In Proceedings of The Twentieth Annual Meeting of The Association for Natural Language Processing (NLP2014), pp. 3-6, Sapporo, Japan, March 17-21.
- Yoko Nakajima, Michal Ptaszynski, Hirotoishi Honma, Fumito Masui. 2014. Investigation of Future Reference Expressions in Trend Information. In Proceedings of the 2014 AAAI Spring Symposium Series, "Big data becomes personal: knowledge into meaning – For better health, wellness and well-being –", pp. 31-38, Stanford, USA, March 24-26, 2014.



# Conclusions and Future Work

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- ✓ Little major development in language modelling
- ✓ None of the models catches the whole picture
- ✓ Presented a novel “pattern-based” language modelling method based on the idea of Language Combinatorics
- ✓ Applied the method to different datasets

In the near future:

- Apply to other data not limited to binary classification
- Analyze the behavior of different classifiers when trained on patterns

# Thank you for your attention!

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