

# Representation Learning - A Case Study

Magdalena Wiercioch

Faculty of Physics, Astronomy and Applied Computer Science & Faculty of  
Mathematics and Computer Science  
Jagiellonian University  
e-mail: [magdalena.wiercioch@uj.edu.pl](mailto:magdalena.wiercioch@uj.edu.pl)

58. Cracow School of Theoretical Physics

Magdalena Wiercioch

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- 1 Introduction
- 2 Methodology no. 1
- 3 Methodology no. 2
- 4 Conclusions

# Problem

## Introduction

Methodology no. 1

Methodology no. 2

Conclusions

“When solving a problem of interest, do not solve a more general problem as an intermediate step. Try to get the answer that you really need but not a more general one.”

# Problem

## Introduction

Methodology no. 1

Methodology no. 2

Conclusions

“When solving a problem of interest, do not solve a more general problem as an intermediate step. Try to get the answer that you really need but not a more general one.”

- Discriminative models are better than generative models.
- It was intended to justify transduction - label the unlabeled point only, not a full model.
- It neglected the structure of the data.

Magdalena Wiercioch

## Introduction

Methodology no. 1

Methodology no. 2

Conclusions

How do humans learn actually?

# Problem

## Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- Kids can recognize their parents.
- They cannot paint them yet.
- This model is far more useful than a perfect reproduction.

# Attributes of representation

## Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- Useful - It can do an inference on what is possible.
- Simple - it skips a lot of details.
- Accurate enough - it enables to recognize and identify novelty.

# Representation Learning - A Case Study

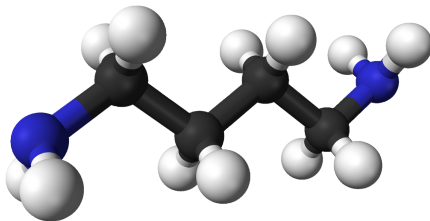
Magdalena Wiercioch

Introduction

**Methodology no. 1**

Methodology no. 2

Conclusions



7/32





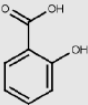
Magdalena Wiercioch

Introduction

Methodology no. 1

Methodology no. 2

Conclusions




n	1	2	3	4	5	6	7	8	9	10
1	0	1	0	0	0	1	0	0	0	0
2		0	1	0	0	0	0	0	0	0
3			0	1	0	0	0	0	0	0
4				0	1	0	0	0	0	0
5					0	1	0	0	0	1
6						0	1	0	0	0
7							0	1	1	0
8								0	0	0
9									0	0
10										0

$$[A(G)]_{ij} = \begin{cases} 1; & i \neq j, e_{ij} \in E(G) \\ 0; & i = j, e_{ij} \notin E(G) \end{cases}$$

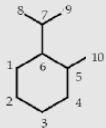
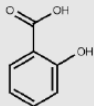
Magdalena Wiercioch

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



n	1	2	3	4	5	6	7	8	9	10
1	0	1	2	3	2	1	2	3	3	3
2		0	1	2	3	2	3	4	4	4
3			0	1	2	3	4	5	5	3
4				0	1	2	3	4	4	2
5					0	1	2	3	3	1
6						0	1	2	2	2
7							0	1	1	3
8								0	2	4
9									0	4
10										0

$$[D(G)]_{ij} = \begin{cases} d_{ij} & ; i \neq j \\ 0 & ; i = j \end{cases}$$

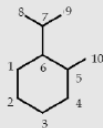
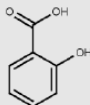
Magdalena Wiercioch

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



n	1	2	3	4	5	6	7	8	9	10
1	0	2				1				
2	2	0	1							
3		1	0	2						
4			2	0	1					
5				1	0	2				1
6	1				2	0	1			
7						1	0	1	2	
8							1	0	1	
9							2		0	
10					1					0

$$[B(G)]_{ij} = \begin{cases} b_{ij} & i \neq j \\ 0 & i = j \end{cases}$$

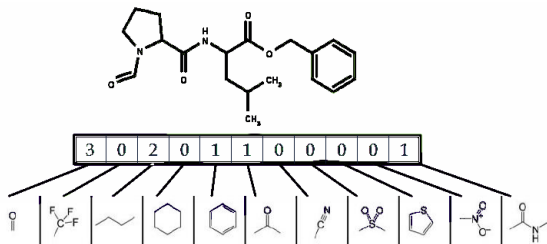
Magdalena Wiercioch

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



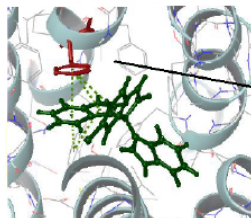
# Structural interaction fingerprint

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



...101010000101010010101010010...



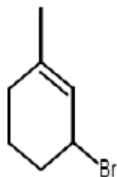
Magdalena Wiercioch

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



(a) CC1=CC(Br)CCC1

(b) CC1=CC(CCC1)Br



```
Mrv0541 01151319442D
10 10 0 0 0 0          999 V2000
-1.6721 -0.1120 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-0.9576 -0.5245 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-0.9576 -1.3495 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-1.6721 -1.7620 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-2.3866 -1.3495 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-2.3866 -0.5245 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-1.6721 0.7130 0.0000 C 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-2.3866 1.1255 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-0.9576 1.1255 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
-0.2432 -0.1120 0.0000 O 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1 2 1 0 0 0 0
 1 6 2 0 0 0 0
 2 3 2 0 0 0 0
 3 4 1 0 0 0 0
 4 5 2 0 0 0 0
 5 6 1 0 0 0 0
 1 7 1 0 0 0 0
 7 8 2 0 0 0 0
 7 9 1 0 0 0 0
 2 10 1 0 0 0 0
M  END
> <CidId>
5
> <Mol Weight>
138.1207
> <Formula>
C7H6O3
9999
```

header

atomic coordinates

connection table

properties



Magdalena Wiercioch

Introduction

**Methodology no. 1**

Methodology no. 2

Conclusions

- Moments are scalar quantities used to characterize a function and to capture its significant features.

6/32



## Definition

General moment  $M_{pq}^{(f)}$  of an image  $f(x, y)$ , gdzie  $p, q$  re non-negative integers and  $r = p + q$  is called the order of the moment, defined as

$$M_{pq}^{(f)} = \iint p_{pq}(x, y) f(x, y) dx dy,$$

where  $p_{00}(x, y), p_{10}(x, y), \dots, p_{kj}(x, y), \dots$  are polynomial basis functions defined on  $D$ .

## Definition

General moment  $M_{pq}^{(f)}$  of an image  $f(x, y)$ , gdzie  $p, q$  re non-negative integers and  $r = p + q$  is called the order of the moment, defined as

$$M_{pq}^{(f)} = \iint p_{pq}(x, y) f(x, y) dx dy,$$

where  $p_{00}(x, y), p_{10}(x, y), \dots, p_{kj}(x, y), \dots$  are polynomial basis functions defined on  $D$ .

Depending on the polynomial basis used, we recognize various systems of moments.

Magdalena Wiercioch

Introduction

**Methodology no. 1**

Methodology no. 2

Conclusions

$p_{kj}(x, y) = x^k y^j$  leads to geometric moments.

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy.$$

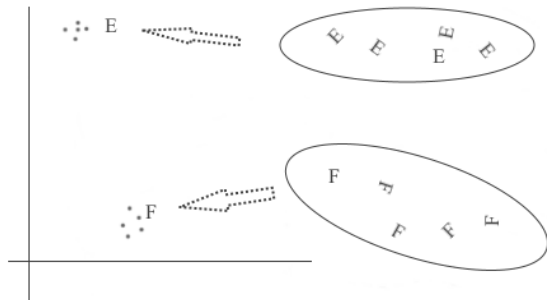
Magdalena Wierciach

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



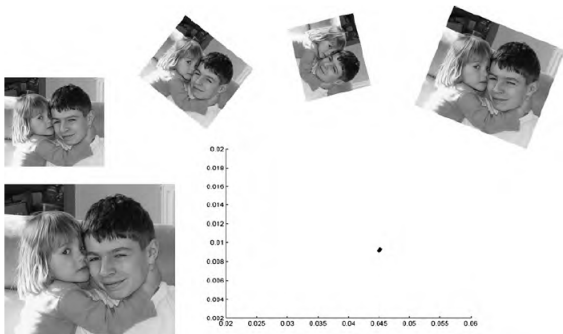
Magdalena Wierciach

Introduction

Methodology no. 1

Methodology no. 2

Conclusions



# Hu invariants - drawbacks

Introduction

**Methodology no. 1**

Methodology no. 2

Conclusions

- mutual dependence;
- restriction to second- and third-order moments only.

# Research motivation

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

PAINTING  
IN



- Piotr Bojanowski, Edouard Grave, Armand Joulin, Tomas Mikolov: *Enriching Word Vectors with Subword Information*, arXiv, 2016.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean: *Efficient estimation of word representations in vector space*, arXiv, 2013.



# Background

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- Scott Deerwester, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, and Richard Harshman: *Indexing by latent semantic analysis*. Journal of the American Society for Information Science, 1990.
- neural networks
- Hinrich Schütze: *Dimensions of meaning*. Proceedings of the 1992 ACM/IEEE Conference on Supercomputing, 1992.
- N. Sakamoto, K. Yamamoto, and S. Nakagawa: *Combination of syllable based n-gram search and word search for spoken term detection through spoken queries and iv/oov classification*. Automatic Speech Recognition and Understanding (ASRU), 2015.

Magdalena Wiercioch

Introduction

Methodology no. 1

**Methodology no. 2**

Conclusions

- We extended the method introduced by Bojanowski et al.
- The model demonstrated by Bojanowski is derived from continuous Skip-gram (SG) model proposed by Mikolov et al.

# Skip-gram model

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- The goal of Skip-gram model is to find word representation that is useful for predicting the surrounding words in a corpus.
- Let us denote the sequence of training words - vocabulary,  $W = \{w_1, w_2, \dots, w_S\}$ , where  $S$  is the size of vocabulary.
- Skip-gram model maximizes the average log probability

$$l(W) = \sum_{t=1}^S \sum_{c \in C_t} \log p(w_c | w_t),$$

where  $C_t$  is the context.

Magdalena Wiercioch

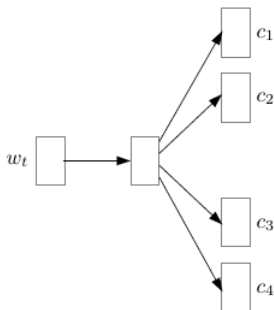
Introduction

Methodology no. 1

Methodology no. 2

Conclusions

input layer   hidden layer   output layer



*...distributed representations of words in a vector space ...*

$c_1$     $c_2$     $w_t$     $c_3$     $c_4$

# Skip-gram model

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- The probability of observing a context word  $w_c$  given  $w_t$  is parametrized using the word vectors.
- Given a scoring function  $s$ , which maps pairs of (word, context) to value in  $\mathbb{R}$ , a possible choice to define the probability of a context word is the softmax.

$$p(\text{Context}|\text{Word}) = y_c = \frac{e^{w_c^\top w_t}}{\sum_{j=1}^S e^{w_j^\top w_t}},$$

where  $w_c$ ,  $w_t$ ,  $w_j$  are vector representations of words and  $y_c$  is the output of the  $c$ -th neuron of the output layer.

- The parametrization for the scoring function is done by taking the scalar product between word and context embeddings:  $s(\text{Word}, \text{Context}) = w_t^\top w_c$ .

# Subword model by Bojanowski et al.

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- The Skip-gram model ignores the internal structure of words.
- They introduced a different scoring function  $s$

$$s(w, c) = \sum_{g \in G_w} z_g^T v_c,$$

where  $G_w = \{1, \dots, G\}$  is the set of letter  $n$ -grams which appear in  $w$ .

# Subword model by Bojanowski et al.

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- The Skip-gram model ignores the internal structure of words.
- They introduced a different scoring function  $s$

$$s(w, c) = \sum_{g \in G_w} z_g^\top v_c,$$

where  $G_w = \{1, \dots, G\}$  is the set of letter  $n$ -grams which appear in  $w$ .

- Limitations:
  - $n$ -grams with a length greater or equal than 3 and smaller or equal than 6 were considered.
  - We claim it may be insufficient for short and rare words.

# Fragmentation model

- Let us denote by  $G_w = \{1, \dots, G\}$  the set of letter  $n$ -grams which appear in  $w$  and  $H_w = \{1, \dots, H\}$  to be the set of syllable  $n$ -grams which appear in  $w$ .



# Fragmentation model

- Let us denote by  $G_w = \{1, \dots, G\}$  the set of letter  $n$ -grams which appear in  $w$  and  $H_w = \{1, \dots, H\}$  to be the set of syllable  $n$ -grams which appear in  $w$ .
- We associate a vector representation  $z_g$  to each letter  $n$ -gram  $g$  and a vector representation  $z_h$  to each syllable  $n$ -gram  $h$ .

# Fragmentation model

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- Let us denote by  $G_w = \{1, \dots, G\}$  the set of letter  $n$ -grams which appear in  $w$  and  $H_w = \{1, \dots, H\}$  to be the set of syllable  $n$ -grams which appear in  $w$ .
- We associate a vector representation  $z_g$  to each letter  $n$ -gram  $g$  and a vector representation  $z_h$  to each syllable  $n$ -gram  $h$ .
- The new word representation is considered as the direct concatenation of the two vector representations of its  $n$ -grams (letter and syllables)

$$z_{new} = [z_g, z_h].$$

# Fragmentation model

Introduction

Methodology no. 1

Methodology no. 2

Conclusions

- Let us denote by  $G_w = \{1, \dots, G\}$  the set of letter  $n$ -grams which appear in  $w$  and  $H_w = \{1, \dots, H\}$  to be the set of syllable  $n$ -grams which appear in  $w$ .
- We associate a vector representation  $z_g$  to each letter  $n$ -gram  $g$  and a vector representation  $z_h$  to each syllable  $n$ -gram  $h$ .
- The new word representation is considered as the direct concatenation of the two vector representations of its  $n$ -grams (letter and syllables)

$$z_{new} = [z_g, z_h].$$

- The scoring function is

$$s(w, c) = \sum_{new \in G_w \cup H_w} z_{new}^T v_c.$$

- The upgraded model makes use of  $n$ -grams of varied length  $n$ .

- Invariance based methods are being tested in order to be applied to objects described by many features.
- The Skip-Gram based method outperforms state-of-the-art approaches on dense languages when tasks such as word similarity ranking or syntactic and semantic analogies are taken into consideration.



gmum.net

TFML 2019 ABOUT FOR STUDENTS SEMINARS TEA SEMINARS TEAM PAPERS CONTACT HARDWARE GMUM.NET



## Group of Machine Learning Research

Welcome at the website of GMUM, the Special Interest Group on Machine Learning created at (but not limited to!) the Faculty of Mathematics and Computer Science of Jagiellonian University.

Learn more



### Achievements

Our prizes, grants and other accomplishments.



### for Students

See what we can offer you, as a Bachelor, Master of PhD level student.



### Research

Interested in our research? Please come in.



### Seminar

Come to our weekly meeting.



### Team

Take a quick tour through our team members.



Thank you.