Workshop on AI & DH
CRIHN, Université de Montréal
Montréal, Canada

Sous les distributions, la structure!

Unearthing structural(ist) features from linguistic distributions

Juan Luis Gastaldi

ETH zürich

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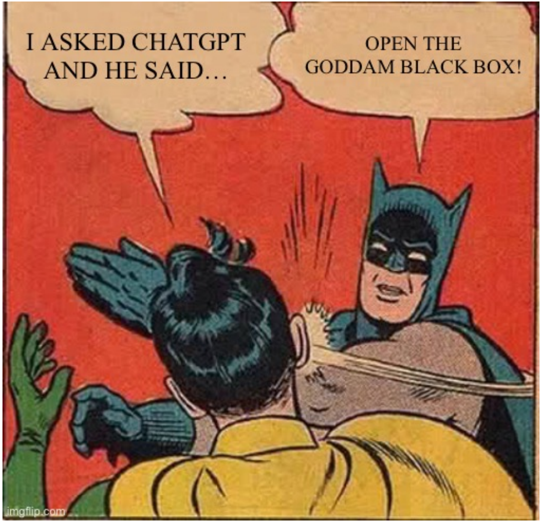
Outline

Outline


I ASKED CHATGPT AND HE SAID…
OPEN THE GODDAM BLACK BOX!
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Introduction

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- When it is not ideologically motivated, the black box narrative relies on a categorical mistake.
  - ML models are not *natural* objects but *formal* objects.

Stochastic Parrots vs. AI Consciousness

📉🦜

Language models are not like us,
therefore they do not and can not have any relation to meaning.

🤖🧠

Language models have a relation to meaning,
therefore they are like us.

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  - What do *we* understand about LLMs ?
  - What can we understand *about language* through them?

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- LLMs tell us something about the Computational Structure of Language

Opening the Black-Box

Subword Tokenization
(Sennrich et al., 2016)

Word Embeddings
(Mikolov, Sutskever, Chen, Corrado, and Dean, 2013)

Self-Attention
(Vaswani et al., 2017)

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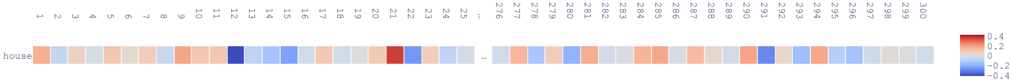
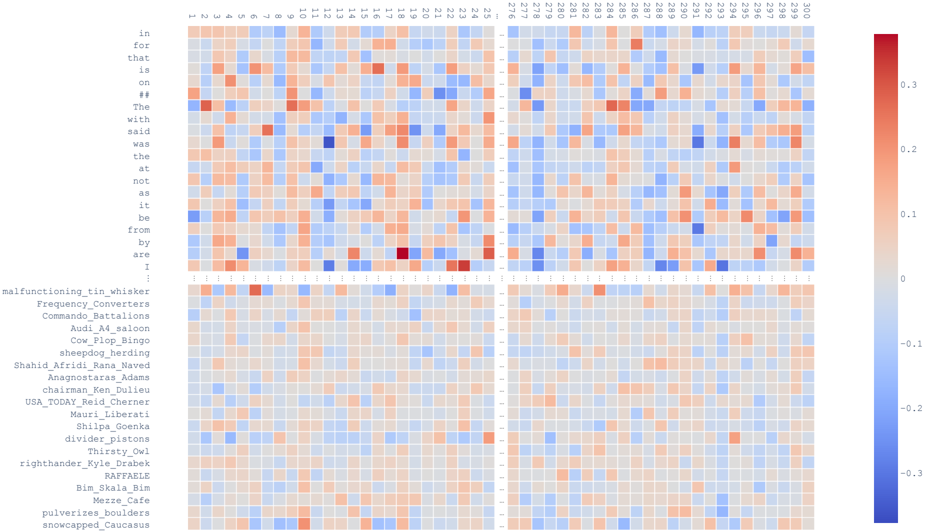
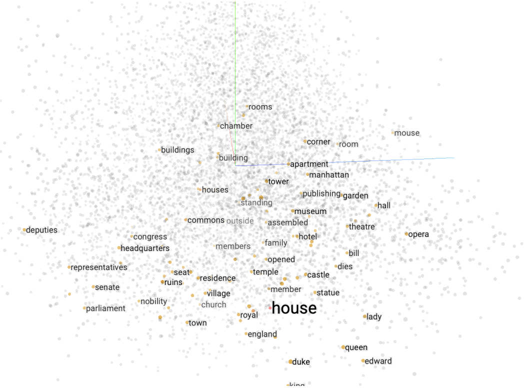
Word Embeddings: Vector



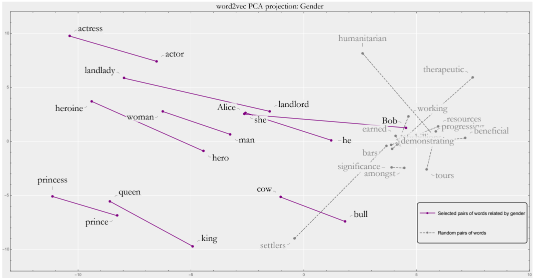
Word Embeddings: Matrix



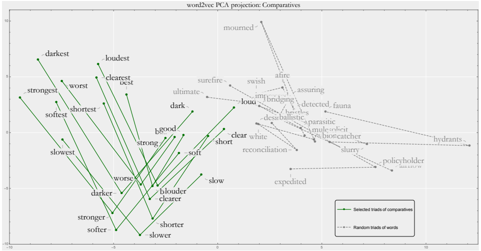
Embedding Space: Similarity and Analogy

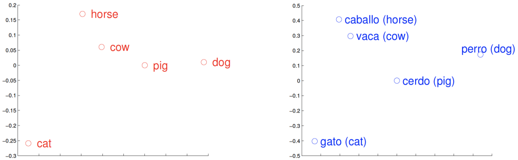


(https://projector.tensorflow.org)

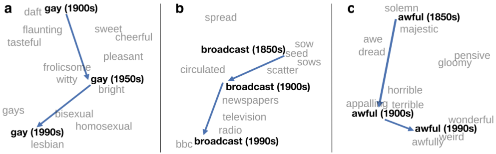


Embedding Space: Other Applications

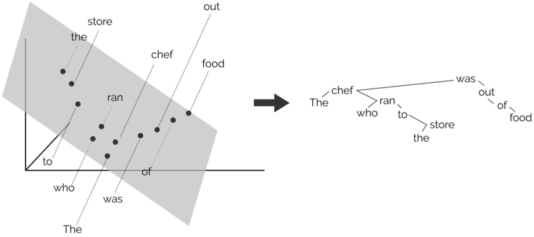




(Mikolov, Sutskever, Chen, Corrado, Dean, et al., 2013)

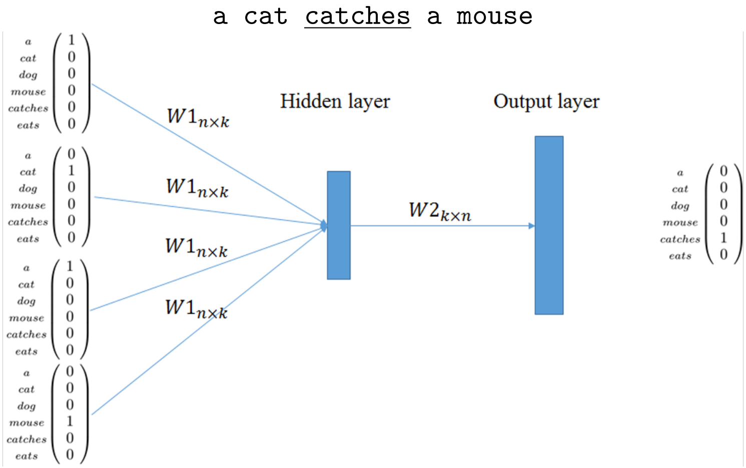


(Hamilton et al., 2016)



(https://nlp.stanford.edu/~johnhew/structural-probe.html)

word2vec Models

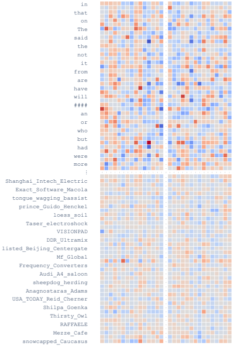


Credit: Ferrone et al., 2017

Outline

word2vec as Implicit Matrix Factorization

(Levy and Goldberg, 2014)



word2vec as Implicit Matrix Factorization

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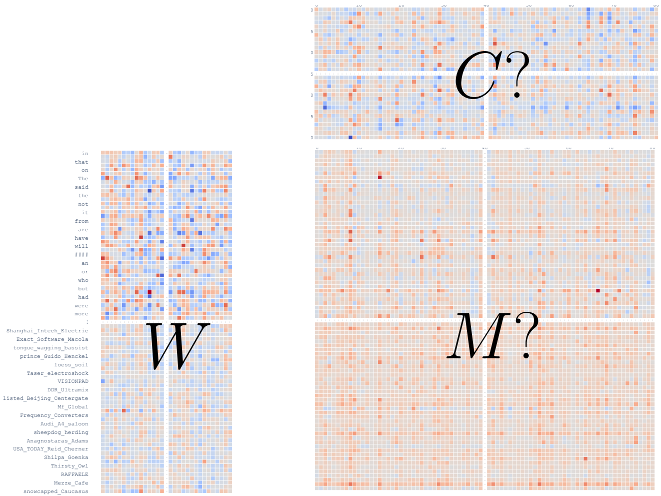

$$W \times C \approx M$$

word2vec Explained

(Levy and Goldberg, 2014)

$$\ell = \sum_{w \in V_w} \sum_{c \in V_c} \#(w, c)\left(\log \sigma(\vec{w} \cdot \vec{c}) + k \cdot \mathbb{E}_{c_N \sim P_D}[\log \sigma(-\vec{w} \cdot \vec{c}_N)]\right)$$

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Three results:

- $M = PMI(w,c) - \log k$ (Pointwise Mutual Information)

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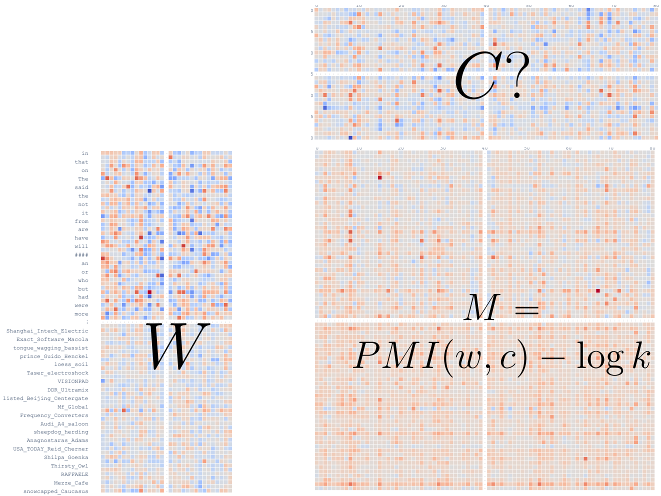
Three results:

- $M = PMI(w,c) - \log k$ (Pointwise Mutual Information)
- W is low dimensional
- The Singular Value Decomposition (SVD) provides an exact solution to find W

Pointwise Mutual Information (PMI)



$$PMI(w, c) = \log \frac{p(w,c)}{p(w)p(c)}$$

Singular Value Decomposition (SVD)

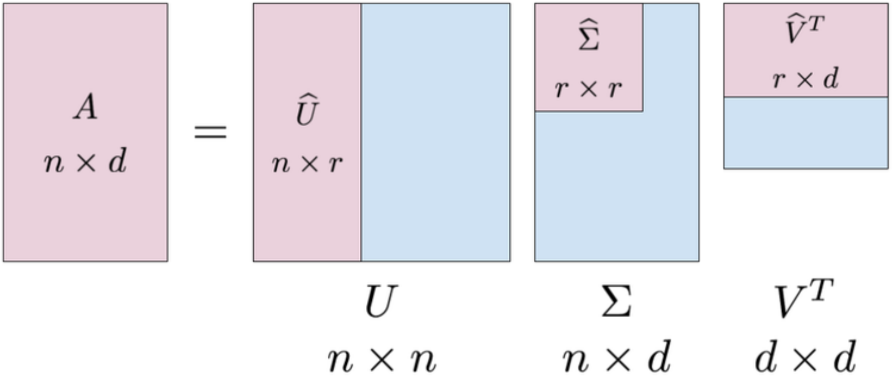
$$M = U\Sigma V^*$$

Where:

$$\begin{aligned} M &= m \times n \text{ (real or complex) matrix} \\ U &= m \times m \text{ unitary matrix} \\ \Sigma &= m \times n \text{ non-negative real rectangular diagonal matrix} \\ V^* &= \text{conjugate transpose of } V\text{, a } n \times n \text{ unitary matrix} \end{aligned}$$

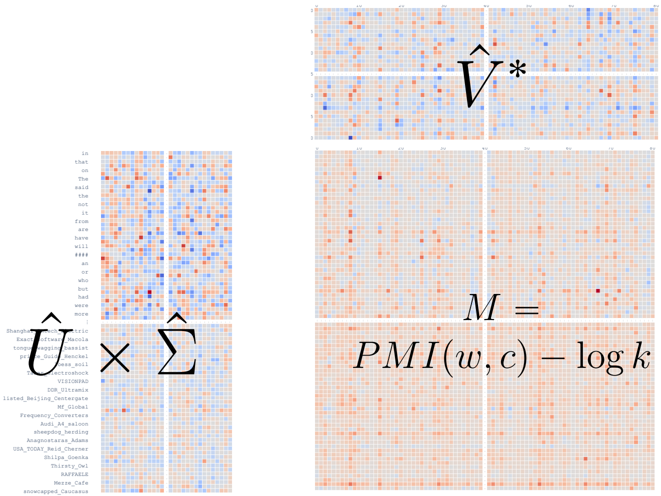
Truncated SVD

$$M = U\Sigma V^*$$



Credit: Angela Ju

Word Embeddings as Truncated SVD

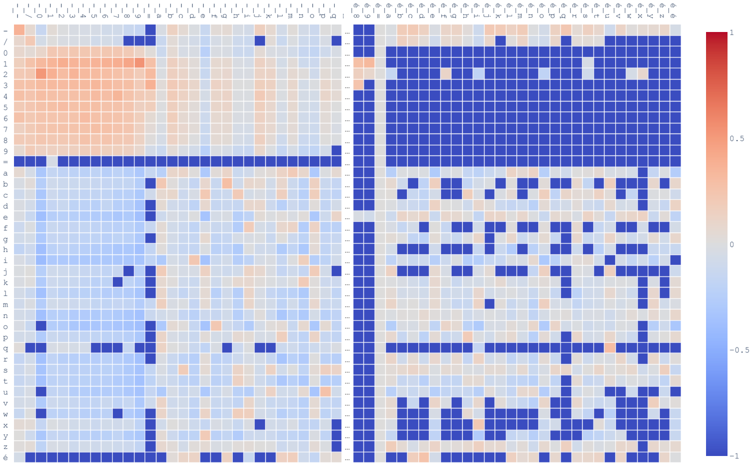


$$M \approx \hat{U} \times \hat{\Sigma} \times \hat{V}^*$$

Outline

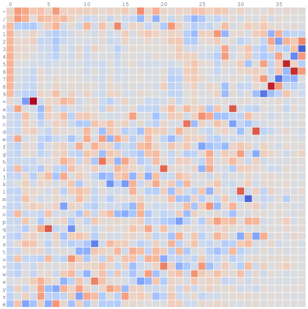
Example: Characters in Wikipedia

$$PMI(w,c) = \log \frac{p(w,c)}{p(w)p(c)}$$

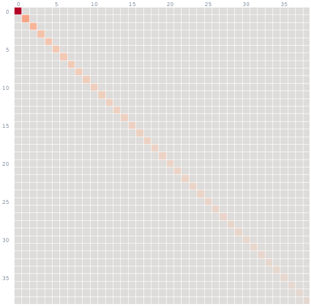


SVD of Wikipedia Character PMI Matrix

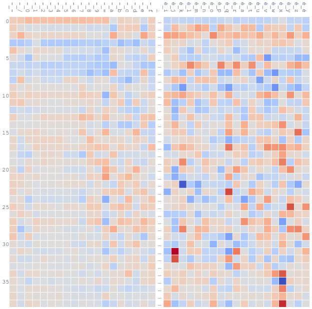
U



Σ

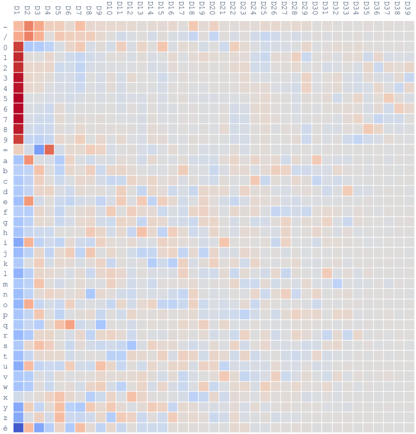


V^*



Truncate and Embed

$$U \times \Sigma$$



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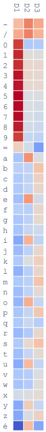
$$\hat{U} \times \hat{\Sigma}$$



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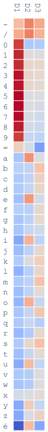
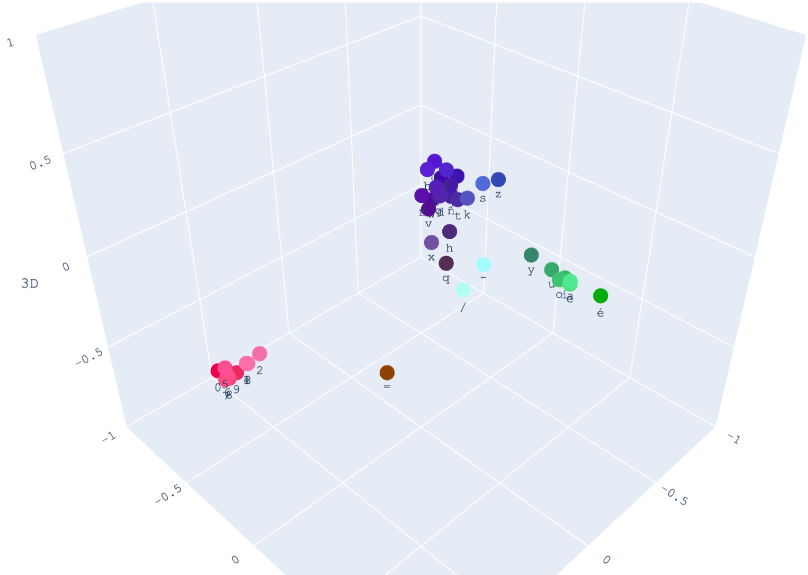




But Why?

4 Why does this produce good word representations?

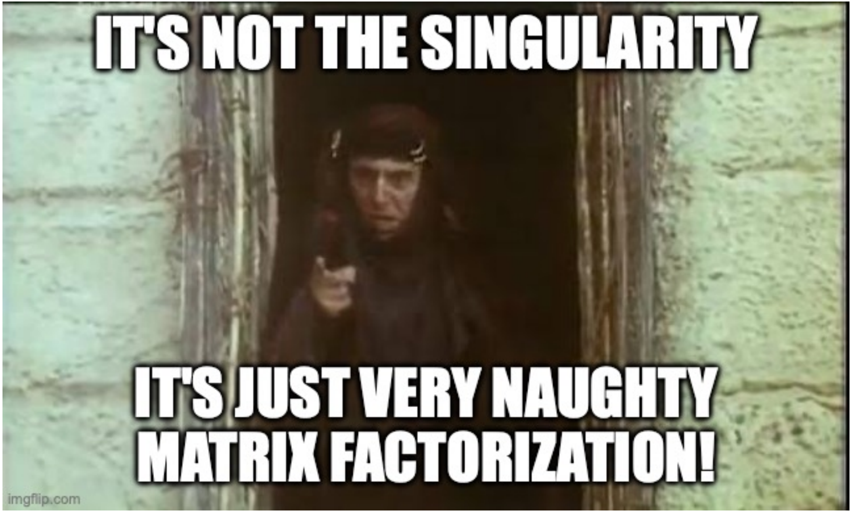
Good question. We don't really know.

The distributional hypothesis states that words in similar contexts have similar meanings. The objective above clearly tries to increase the quantity $v_w \cdot v_c$ for good word-context pairs, and decrease it for bad ones. Intuitively, this means that words that share many contexts will be similar to each other (note also that contexts sharing many words will also be similar to each other). This is, however, very hand-wavy.

Can we make this intuition more precise? We'd really like to see something more formal.

(Goldberg and Levy, 2014)

But Why?


IT'S NOT THE SINGULARITY
IT'S JUST VERY NAUGHTY
MATRIX FACTORIZATION!
imgflip.com

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Where:

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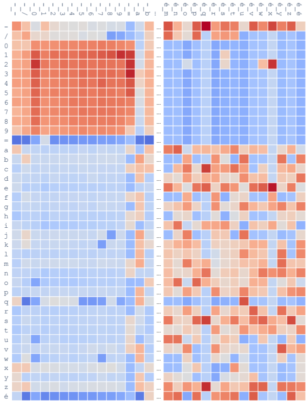
In particular:

- The columns of U (left singular vectors) are eigenvectors of MM^*
- The rows of V^* (right singular values) are eigenvectors of M^*M
- The non-zero elements of Σ (non-zero singular values) are the square roots of the non-zero eigenvalues of MM^* or M^*M

$M \times M^*$ as a Covariance Matrix



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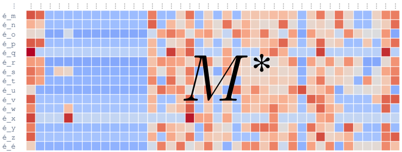

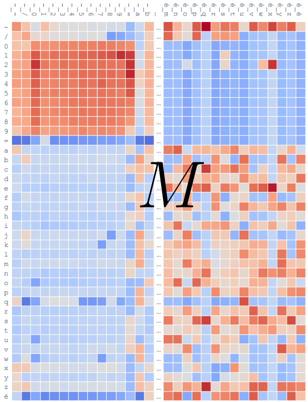

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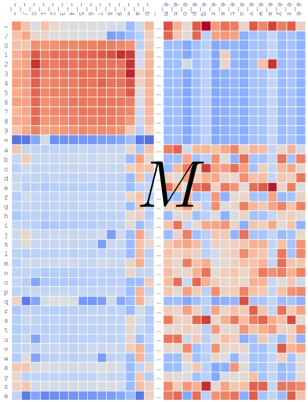
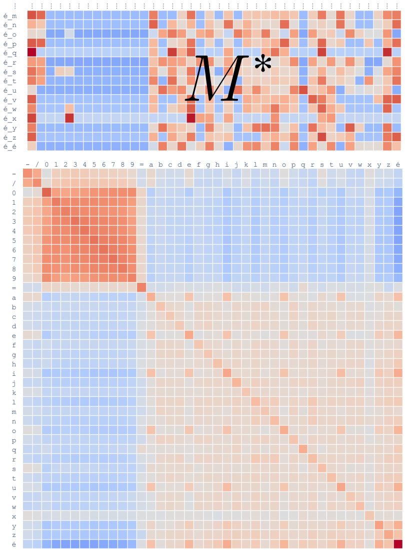
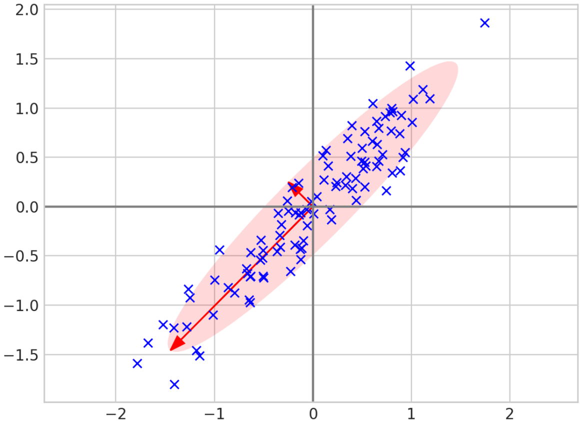




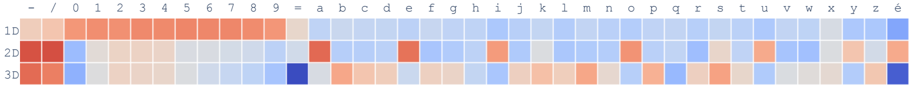
Eigenvectors and Eigenvalues



Credit: Joel Laity

Structural Features

Eigenvectors of $M \times M^*$:



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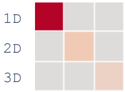
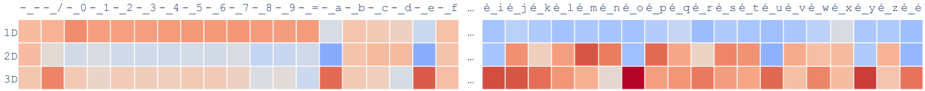


Eigenvectors of $M^* \times M$:



Eigenvectors as Fixed Points

$$(M \times M^*)v = \lambda v$$

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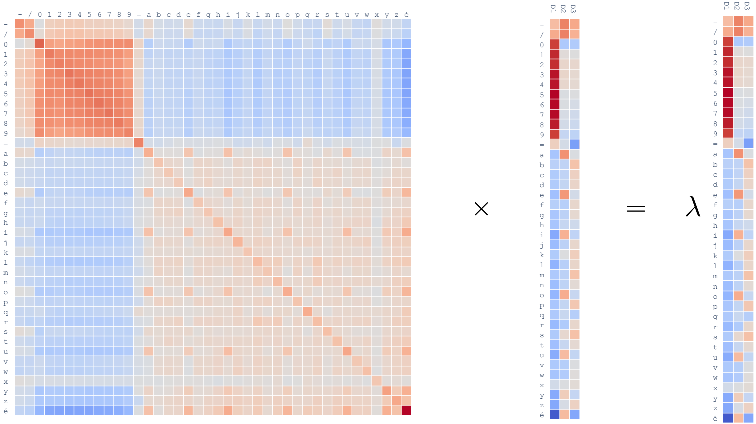
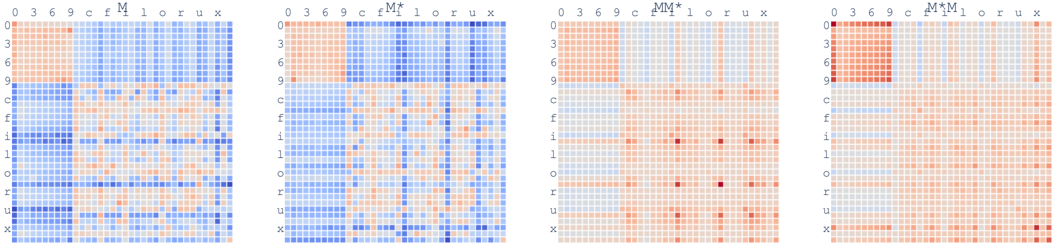


Binary Matrices

$$(M_t \star M_t^*) \star v = v$$



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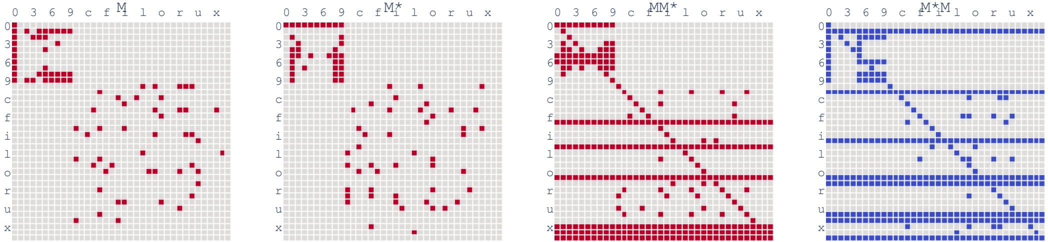

Binary Fixed Points

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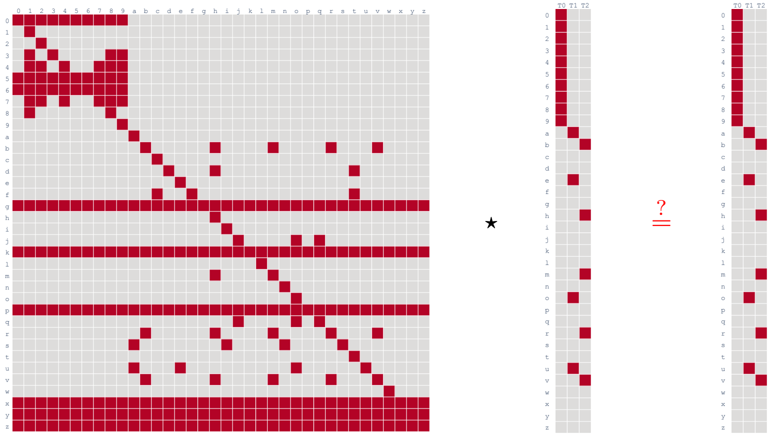
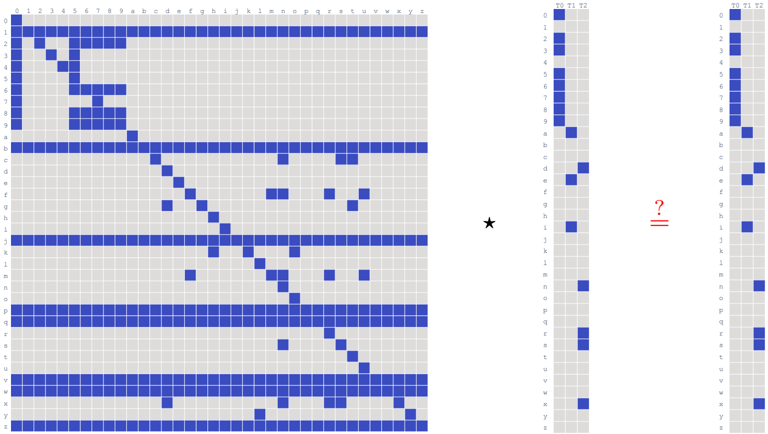


Binary Fixed Points

$$(M_t^* \star M_t) \star \textcolor{red}{v} = \textcolor{red}{v}$$



"Eigensets"

$$(M_t \star M_t^*) \star v = v$$

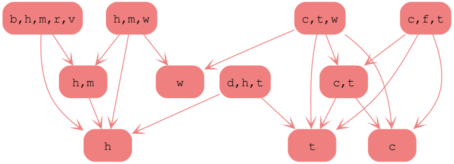
0,1,2,3,4,5,6,7,8,9	1,2,4,7,8,9	b,h,m,r,v	a,e,i,o	a,e,o,u	a,i,n,s	1,3,8,9
1,2,8	h,m,w	1,8,9	d,h,t	j,o,q	c,f,t	c,t,w
a,e,o	a,e,i	h,m	2,9	a,i	w	1,9
1,8	a,e	l	t	n	c	h
2	i	e	a	o	1	9
e,n	a,l	c,t				

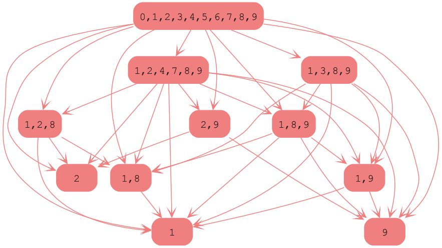
“Eigensets”

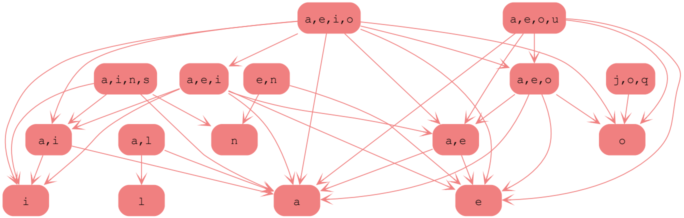
$$(M_t^* \star M_t) \star {\color{red}v} = {\color{red}v}$$

0,2,4,5,6,7,8,9	0,2,3,5,6,7,8,9	0,2,5,6,7,8,9	0,4,5,6,7,8,9	0,5,6,7,8,9	d,n,r,s,x	f,m,n,r,u
l,n,r,s,t	c,n,s,t	0,3,4,5	h,i,o	n,r,s	a,e,i	h,k,o
0,4,5	n,s,t	d,g,t	0,3,5	a,e	a	l,y
i	u	n	e	r	o	d
h	t	l	0	a,h	0,5	n,r
0,7	n,s	h,o				

Which Structure?







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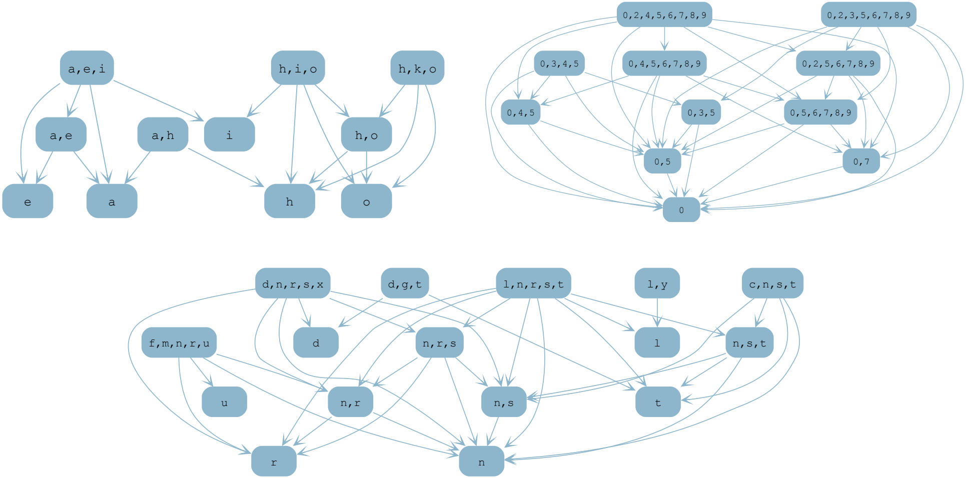
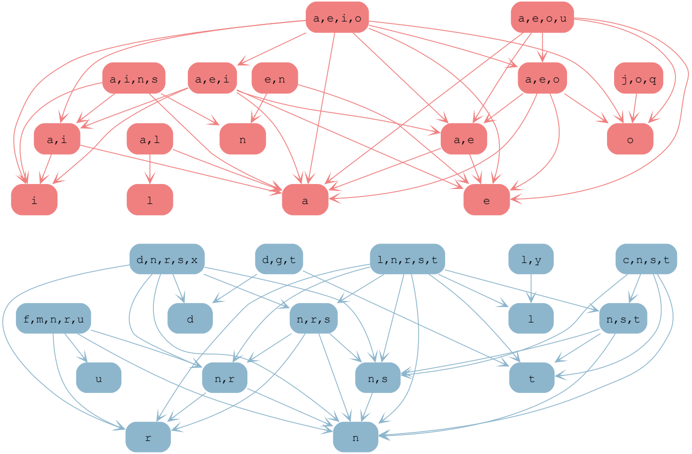


Which Structure?



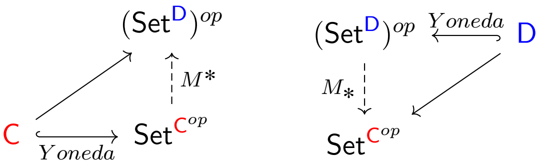
Which Structure?

Profunctor

$f : \mathsf{C}^{\mathrm{op}} \times \mathsf{D} \to \mathsf{Set}$

$\mathsf{C} \to \left(\mathsf{Set}^{\mathsf{D}}\right)^{\mathrm{op}}$

$\mathsf{D} \to \mathsf{Set}^{\mathsf{C}^{\mathrm{op}}}$



$M^* : \mathsf{Set}^{\mathsf{C}^{\mathrm{op}}} \to (\mathsf{Set}^{\mathsf{D}})^{\mathrm{op}}$

$M_* : (\mathsf{Set}^{\mathsf{D}})^{\mathrm{op}} \to \mathsf{Set}^{\mathsf{C}^{\mathrm{op}}}$

$M^* c_i \cong d_i$ and $M_* d_i \cong c_i$.

Isbell adjunction

$M^* : \mathsf{Set}^{\mathsf{C}^{\mathrm{op}}} \leftrightarrows (\mathsf{Set}^{\mathsf{D}})^{\mathrm{op}} : M_*$

(Bradley et al., 2024)

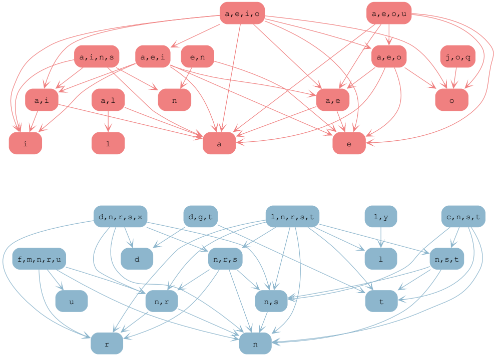
Outline

Definition (Polar/Orthogonal - Girard, 2011)

[G]iven a binary operation, noted $a, b \rightsquigarrow \langle a|b \rangle : A \times B \to C$ and a subset $P \subset C$ (the 'pole') one can define the *polar* $X^{\perp} \subset B$ of a subset $X \subset A$ (resp. $Y^{\perp} \subset A$ of a subset $Y \subset B$) by :

$$X^{\perp} := \{y \in B : \forall x \in X, \langle a|b \rangle \in P\}$$
$$Y^{\perp} := \{x \in A : \forall y \in Y, \langle a|b \rangle \in P\}$$

- The map 'polar' is decreasing: $X \subset X' \Rightarrow X'^{\perp} \subset X^{\perp}$.
- The set Pol$(A) \subset \mathcal{P}(A)$ of *polar* sets, i.e., of the form $Y^{\perp}$, is closed under arbitrary intersections. In particular, A is polar and $X^{\perp\perp}$ is the smallest polar set containing X.
- As a consequence, $X^{\perp\perp\perp} = X^{\perp}$.



Theory of Computational Types

Definition (Polar/Orthogonal - Girard, 2011)

[G]iven a binary operation, noted $a, b \rightsquigarrow \langle a|b\rangle : A \times B \rightarrow C$ and a subset $P \subset C$ (the 'pole') one can define the *polar* $X^{\perp} \subset B$ of a subset $X \subset A$ (resp. $Y^{\perp} \subset A$ of a subset $Y \subset B$) by :

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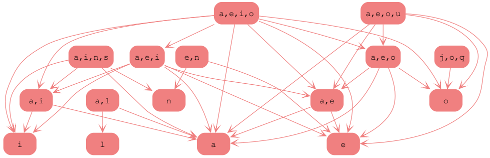

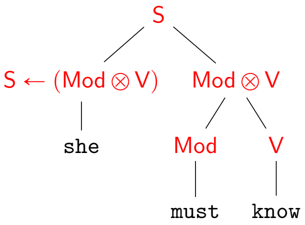

(Gastaldi and Pellissier, 2021)

Outline

Structuralist Semiology: Language (*Langue*) and Text

A Language [...] is the Paradigmatic of a Denotative Semiotic whose Paradigms are Manifested by all Purports.

(Hjelmslev, 1975, Df. 38)

A Text [...] is the Syntagmatic of a Denotative Semiotic whose Chains are Manifested by all Purports.

(Hjelmslev, 1975, Df. 39)

Structuralist Semiology: Language (*Langue*) and Text

A Language [...] is the Paradigmatic of a Denotative Semiotic whose Paradigms are Manifested by all Purports.

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A Text [...] is the Syntagmatic of a Denotative Semiotic whose Chains are Manifested by all Purports.

(Hjelmslev, 1975, Df. 39)

A Paradigmatic or Sign-System [...] is a Semiotic System.

(Hjelmslev, 1975, Df. 35)

A Syntagmatic or Sign-Process [...] is a Semiotic Process.

(Hjelmslev, 1975, Df. 33)

Structuralist Semiology: Semiotic

A Semiotic [...] is a Hierarchy, any of whose Components admits of a further Analysis into Classes defined by mutual Relation, so that any of these classes admits of an analysis into Derivates defined by mutual Mutation.

(Hjelmslev, 1975, Df. 24)

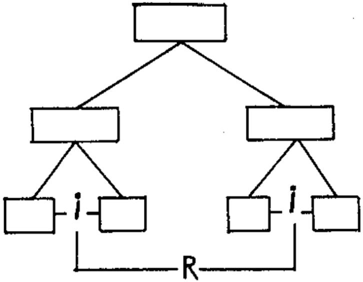
Structuralist Semiology: Semiotic

A Semiotic [...] is a Hierarchy, any of whose Components admits of a further Analysis into Classes defined by mutual Relation, so that any of these classes admits of an analysis into Derivates defined by mutual Mutation.

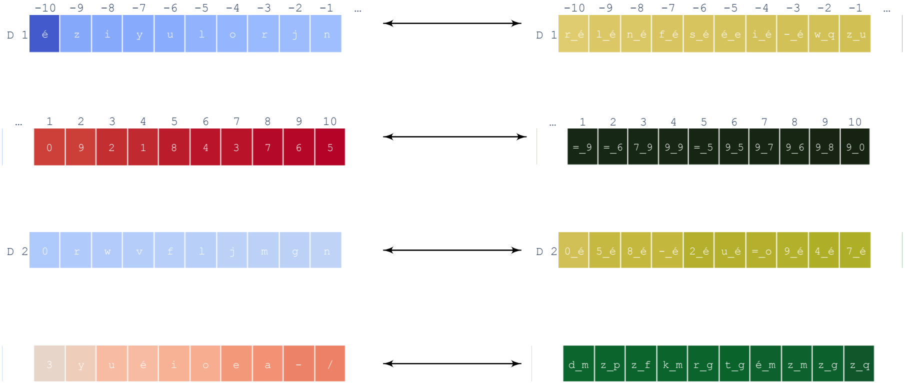
(Hjelmslev, 1975, Df. 24)

Mutation [...] is a Function existing between first-Degree Derivates of one and the same Class, *a function that has Relation to a function* between other first-degree derivates of one and the same class and belonging to the same Rank.

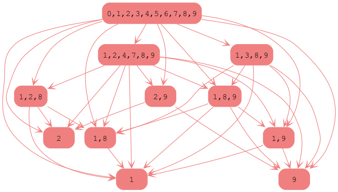
(Hjelmslev, 1975, Df. 23)

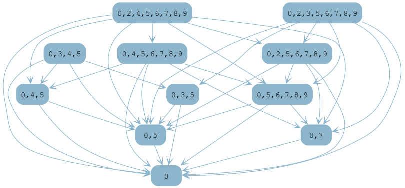


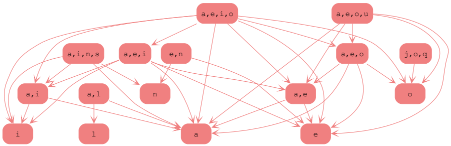
Syntagmatic and Text (Vectors)

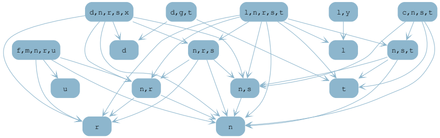


Syntagmatic and Text (Nucleai/Types)

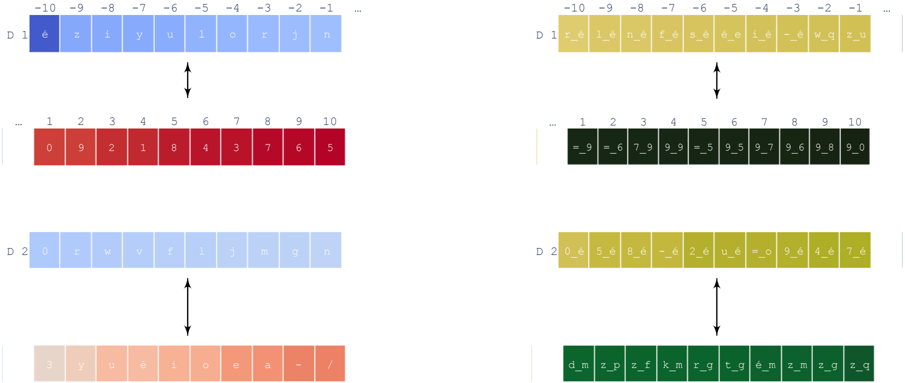




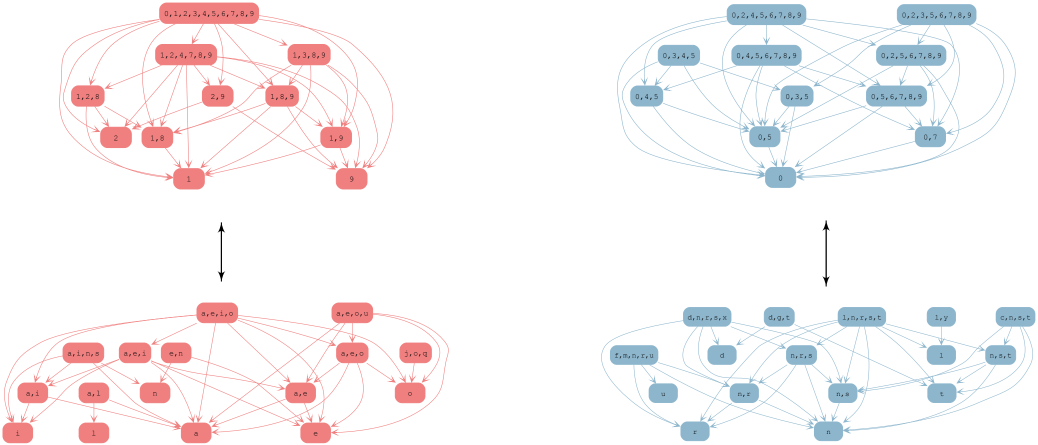




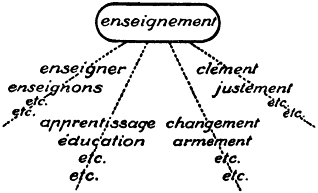
Paradigmatic and *Langue* (Vectors)



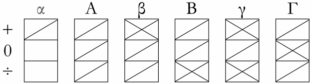
Paradigmatic and *Langue* (Nucleai/Types)



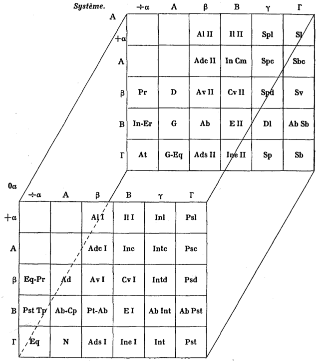
Structuralism and Formalism



(Saussure, 1980)



(Hjelmslev, 1975)



(Hjelmslev, 1935)

Segments	Environments											
	#— r̯	#—r	#—l	e i —C	æ—C	a o u —C	s— e i	s—æ	s— a o u	...	t̯ —	C^3—
t̯	√											
t		√		√	√	√	√	√	√			
K						√			√			
k		√	√		√			√				
ᴋ				√			√					
G						√						
g		√	√		√							
ɢ				√								
r				√	√	√						√
r̯											√	

(Harris, 1960)

Structuralism and Formalism

	a	b	d	e	f	g	h	i
a	aa	ab	ad		af	ag	ah	
b	ba							bi
d	da			de				di
e		eb	ed			eg		
f				fe				
g								gi
h	ha							hi
i			id				ih	i

Diagram 1.

	b	d	f	g	h	a	e	i
f						**fa**	fe	
h						ha		hi
g						**ga**	**ge**	gi
b						ba	**be**	bi
d						da	de	di
a	ab	ad	af	ag	ah	aa		
e	eb	ed	**ef**	eg				
i	**ib**	id		**ig**	ih			i

Diagram 3.

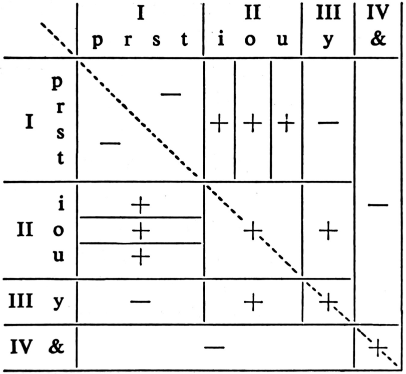


Diagram 2.

(SpangHanssen1959)

Table 8.
Vowel × binary final cluster (cf. sect. 84).

	ft	gt	ks	ds	vn	vl	dr!	mp	nk	ng	nd	nt	ns	lk	ld	lt	rk	rd	rt	rn	S	T	jC	
a	5	10	6	3	9	8	6	8	16	20	14	9	6	9	8	11	7	1	9	3	168	281	3	a
e	–	–	3	1	3	2	2	1	–	4	7	5	6	–	3	5	–	1	3	3	49	95	33	e
i	7	6	9	5	–	1	2	4	13	11	20	8	3	2	11	6	6	1	1	–	116	171	–	i
o	3	2	2	5	4	2	1	1	1	2	3	2	–	4	13	3	6	9	10	4	77	120	–	o
u	2	9	5	4	–	–	6	12	8	4	12	3	2	4	8	4	4	–	2	–	89	143	–	u
y	–	2	–	2	–	–	1	2	4	7	6	2	–	1	6	6	3	2	1	–	45	56	–	y
æ	4	11	1	–	4	4	2	2	9	11	8	1	3	2	11	4	6	6	6	4	99	145	–	æ
ø	5	2	–	–	1	4	–	–	–	–	1	2	3	–	–	–	3	–	1	6	28	47	10	ø
aa	–	–	–	1	–	–	1	–	–	–	4	–	–	–	–	–	–	2	–	1	9	11	–	aa
	26	42	26	21	21	21	21	30	51	59	75	32	23	22	60	39	35	22	33	21	680	1069	46	

(SpangHanssen1959)

Formal Content

(Gastaldi and Pellissier, 2021;Gastaldi, Forthcoming 2024c)

Form ~~vs.~~ and ~~Meaning~~ Content

Kant, Hegel, Frege, Saussure, Hjelmslev, etc.

Formal Content: The dimension of content which finds its source in the internal relations holding between the expressions of a language.

Formal Content

(Gastaldi and Pellissier, 2021;Gastaldi, Forthcoming 2024c)

Form ~~vs.~~ and ~~Meaning~~ Content

Kant, Hegel, Frege, Saussure, Hjelmslev, etc.

Formal Content: The dimension of content which finds its source in the internal relations holding between the expressions of a language.

- *Characteristic Content*: The content resulting from the inclusion of a unit in a class of other units by which it accepts to be substituted in given contexts
- *Syntactic Content*: The content a unit receives as a result of the multiple dependencies it can maintain with respect to other units in its context
- *Informational Content*: The content related to the non-uniform distribution of units within those substitutability classes

Illustration of Formal Contents

(Gastaldi and Pellissier, 2021;Gastaldi, Forthcoming 2024c)

Characteristic Content	Syntactic Content	Informational Content
`{cat, dog, spider, gavagai}`	`“the gavagai is on the mat”`	`{cat:0.059%, dog:0.012%, spider:0.009% gavagai:0.000%}`
Atomic Type	Profunctor Nucleus	Probability Distribution

Formal Interpretability

Subword Tokenization
(Sennrich et al., 2016)

Word Embeddings
(Mikolov, Sutskever, Chen, Corrado, and Dean, 2013)

Self-Attention
(Vaswani et al., 2017)

Formal Interpretability

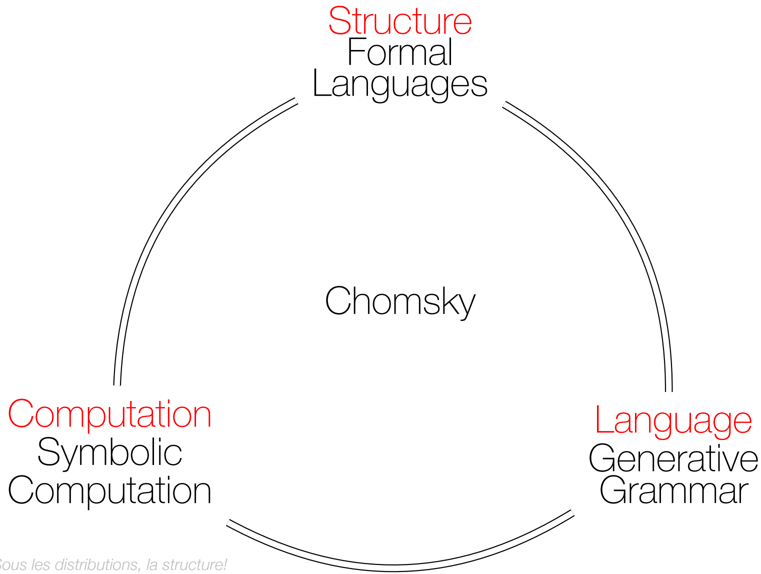
Subword Tokenization
(Sennrich et al., 2016)
Informational Content

Word Embeddings
(Mikolov, Sutskever, Chen, Corrado, and Dean, 2013)
Characteristic Content

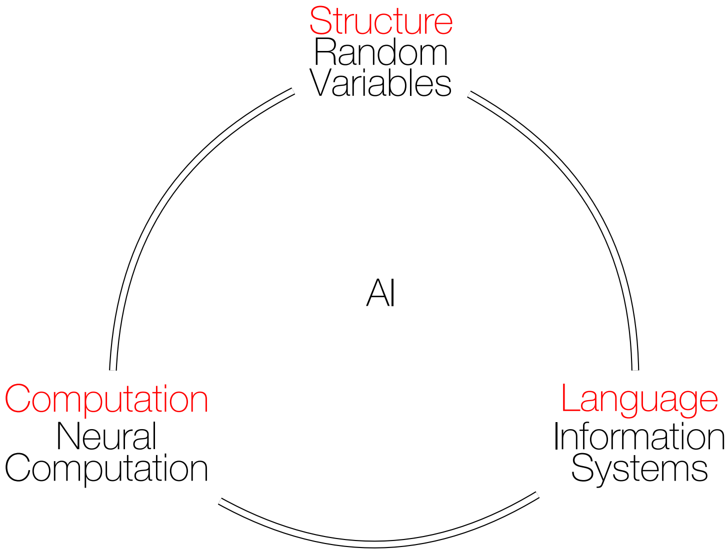
Self-Attention
(Vaswani et al., 2017)
Syntactic Content

Outline

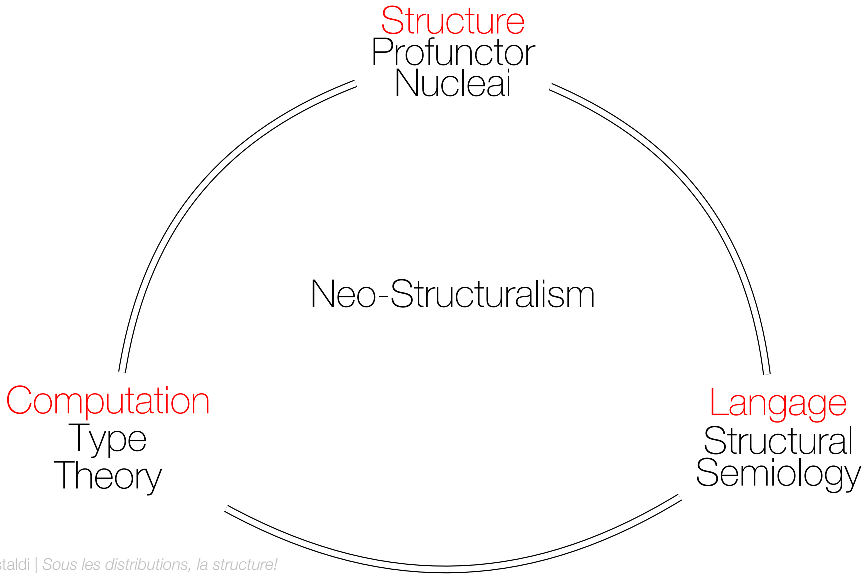
Conclusion


Structure
Formal
Languages
Chomsky
Computation
Symbolic
Computation
Language
Generative
Grammar

Conclusion


Structure
Random Variables
AI
Computation
Neural Computation
Language
Information Systems

Conclusion


Structure
Profunctor
Nucleai
Neo-Structuralism
Computation
Type
Theory
Langage
Structural
Semiology

Collaborations

J. Terilla (CUNY), T.-D. Bradley (SandboxAQ), L. Pellissier (Paris-Est Créteil), Th. Seiller (CNRS), S. Jarvis (CUNY)

Reference Papers

- Gastaldi, J. L. (2020).Why can computers understand natural language?: The structuralist image of language behind word embeddings. *Philosophy & Technology*
- Gastaldi, J. L., & Pellissier, L. (2021).The calculus of language: Explicit representation of emergent linguistic structure through type-theoretical paradigms. *Interdisciplinary Science Reviews*. https://doi.org/10.1080/03080188.2021.1890484
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Workshop on AI & DH
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Montréal, Canada

Sous les distributions, la structure!

Unearthing structural(ist) features from linguistic distributions

Juan Luis Gastaldi

ETH zürich

November 28, 2024