Learning with Partially Ordered Representations

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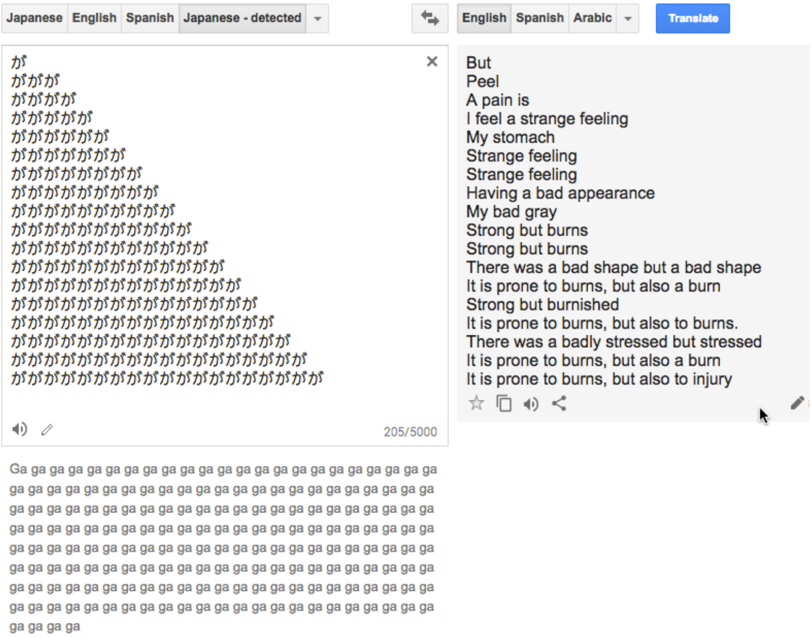
Thank you for the support!

Output in 2018-2019

- Journal Articles: 1 published, 1 in review
- Paper-Reviewed proceedings: 2
- Abstract-reviewed proceedings: 2
- Invited Talks: 6
- Conference Talks: 11
- Conference Posters: 1

The Main Idea

Learning is eased when shared properties of the domain structure the space of hypotheses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English Spanish Arabic
Translate
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ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga
ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga ga
ga ga ga ga
But
Peel
A pain is
I feel a strange feeling
My stomach
Strange feeling
Strange feeling
Having a bad appearance
My bad gray
Strong but burns
Strong but burns
There was a bad shape but a bad shape
It is prone to burns, but also a burn
Strong but burnished
It is prone to burns, but also to burns.
There was a badly stressed but stressed
It is prone to burns, but also a burn
It is prone to burns, but also to injury

Poverty of the Stimulus and Data Sparsity

Number of English words: $N \sim 10000$
Possible English 2-grams: $N^2 = 100000000$
Possible English 3-grams: $N^3 = 1000000000000$
Possible English 4-grams: $N^4 = 10000000000000000$
$\ldots$
easy learning if normal distribution

Poverty of the Stimulus and Data Sparsity

BUT:

In the million-word Brown corpus of English:
45% of words,
80% of 2-grams
95% of 3-grams
appear EXACTLY ONCE
Bad for learning: Huge long-tailed distribution

How can a machine know that new sentences like
"nine and a half turtles yodeled" is good?
"turtles half nine a the yodeled" is bad?

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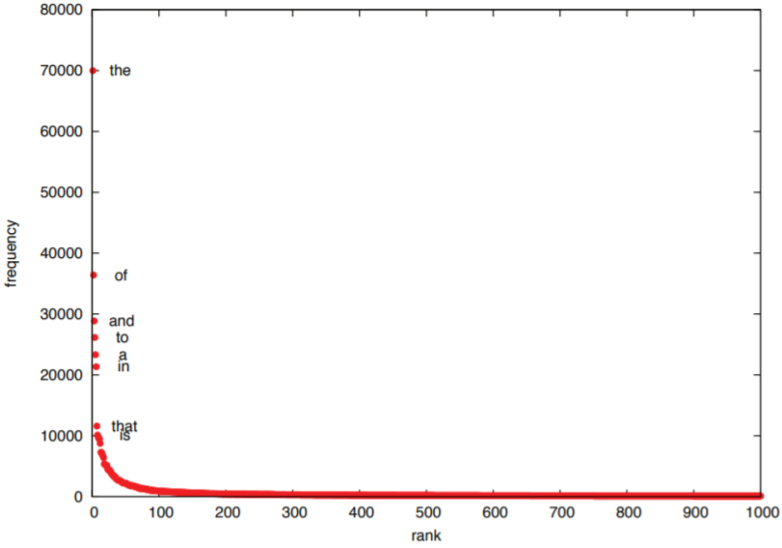
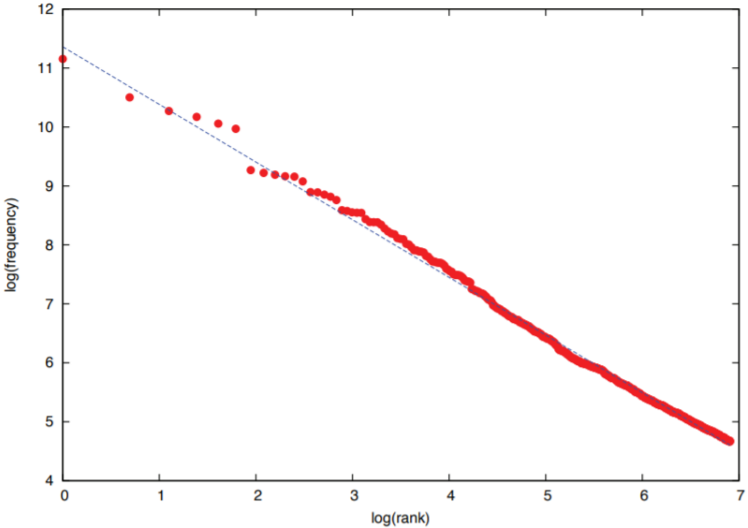
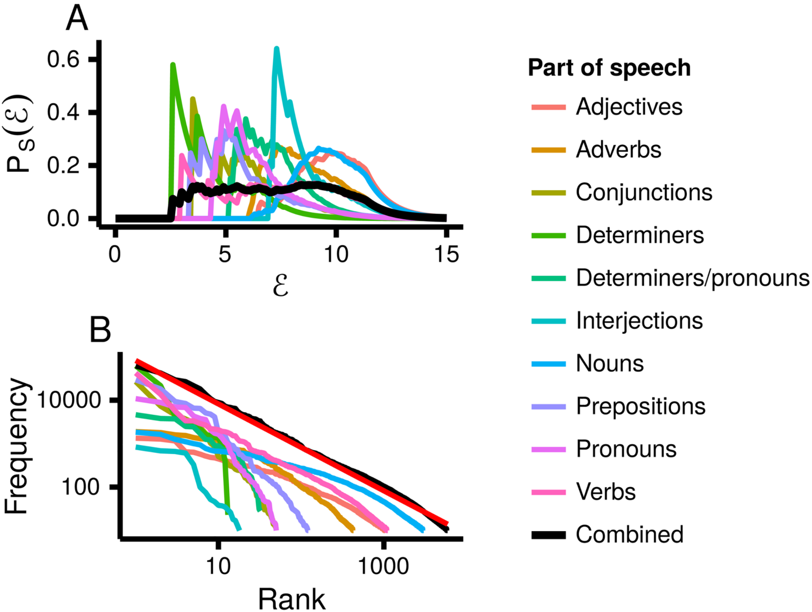
The Zipf Problem



The Zipf Problem



Zipf Emerges from Latent Features



NLP Example

In many NLP applications, text symbols are treated independently

Alphabet $= \{\mathtt{a}, \ldots, \mathtt{z}, \mathtt{A}, \ldots, \mathtt{Z}\} = 52$ symbols

Forbidding maybe all capitals $\rightarrow$ Explosion!

If we use feature [`capital`], only 27! 26 letters + [`capital`]

Learning Algorithm (Chandlee et al 2018)

What have we done so far?

- Provably correct relational learning algorithm
- Prunes Hypothesis space according to ordering relation
- Provably identifies correct constraints for sequential data
- Uses data sparsity to its advantage!

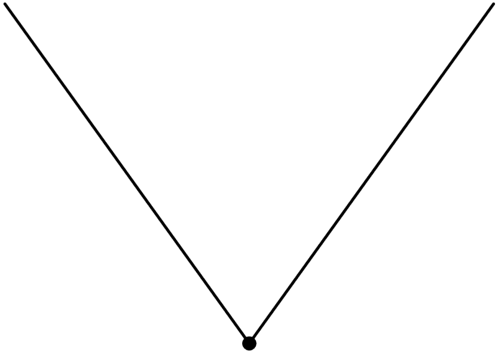
Collaborative work with:

Jane Chandlee (Haverford)

Jeff Heinz (SBU)

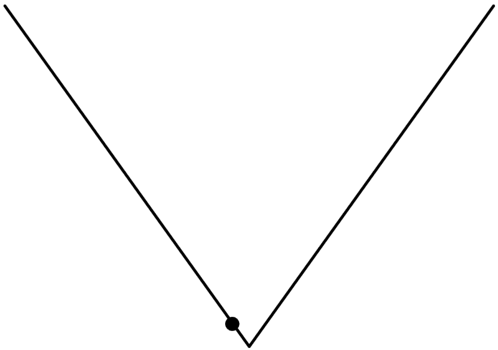
Adam Jardine (Rutgers)

2D Schema of a Semilattice of Constraints



Is this sub-structure in the data sample?

2D Schema of a Semilattice of Constraints



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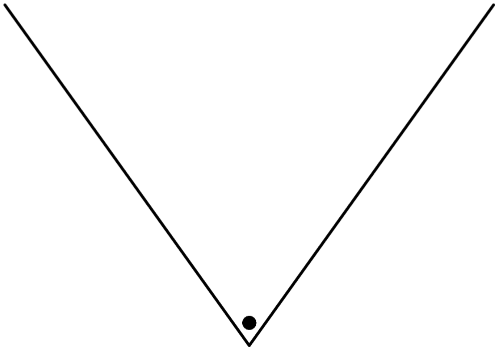

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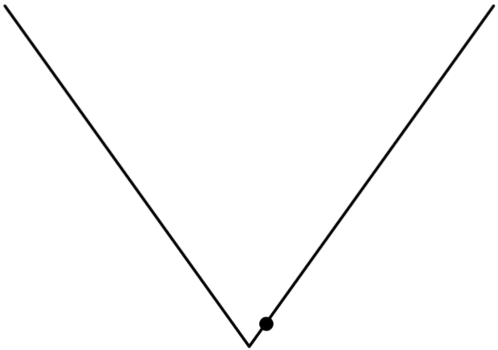

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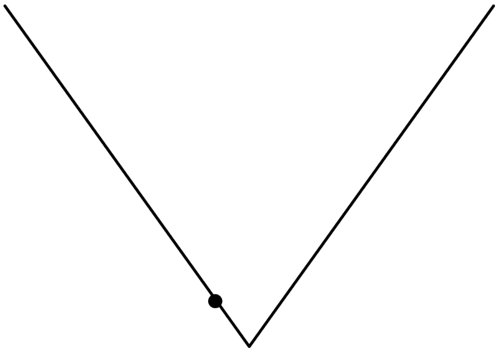

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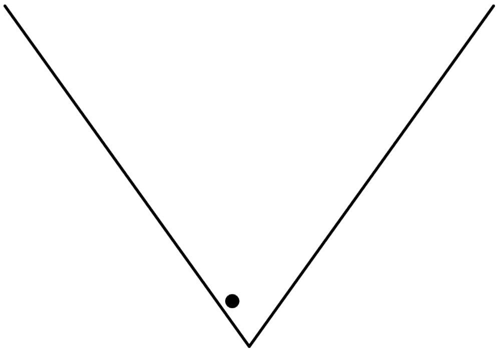

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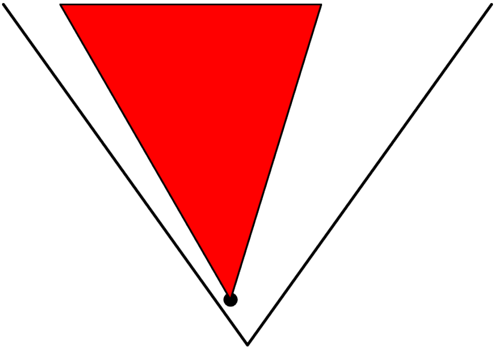

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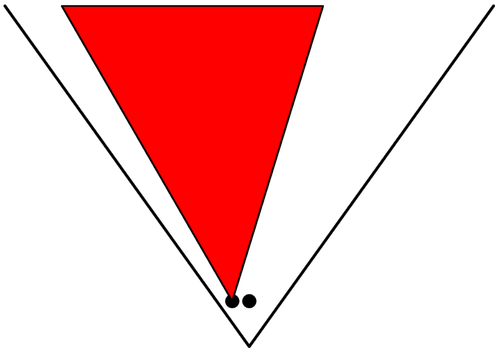

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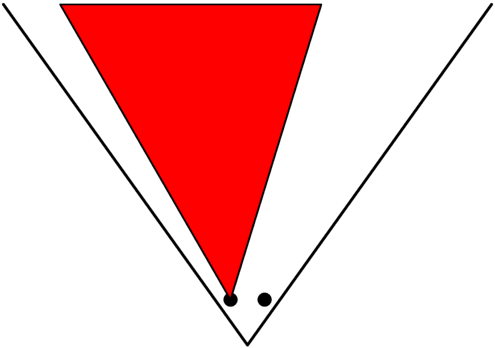

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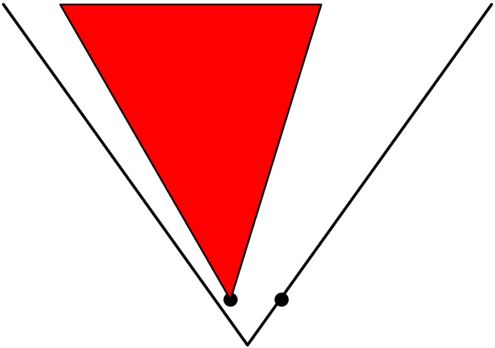

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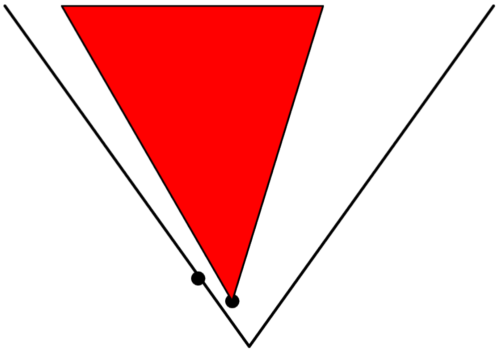

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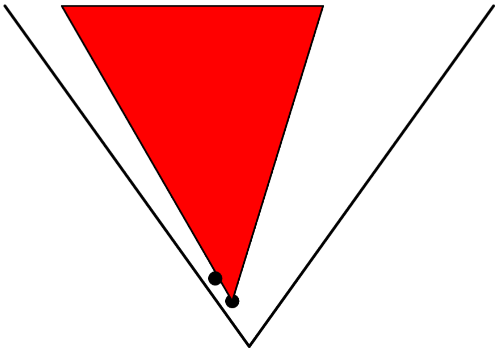

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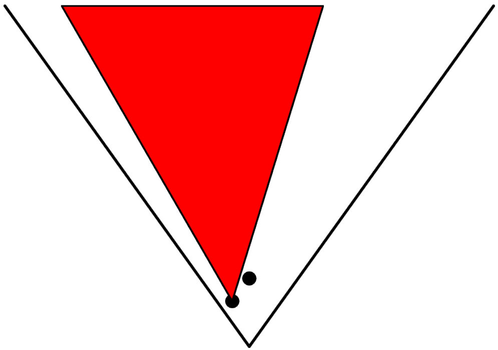

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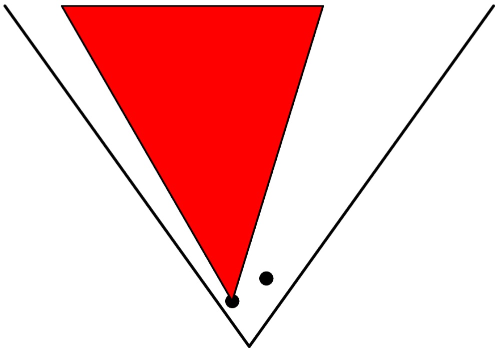

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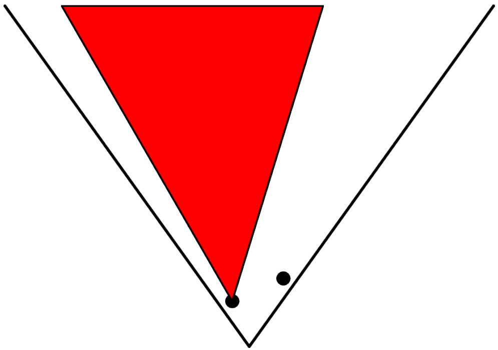

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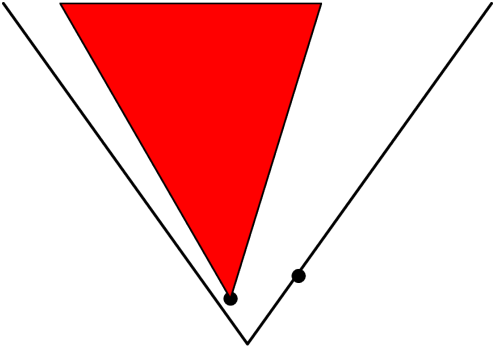

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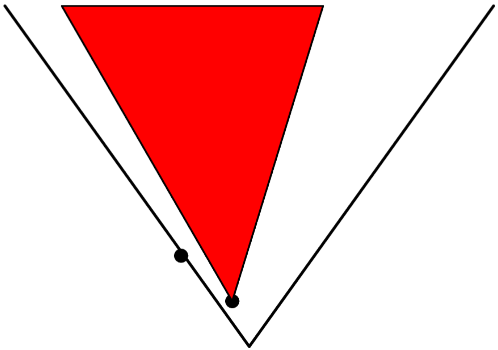

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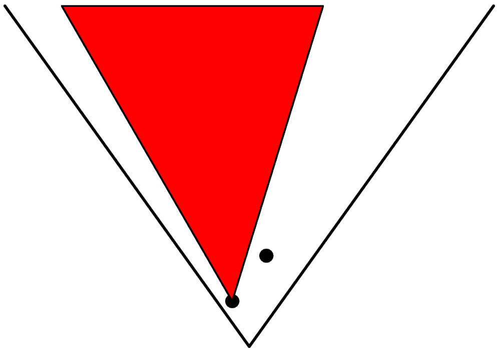

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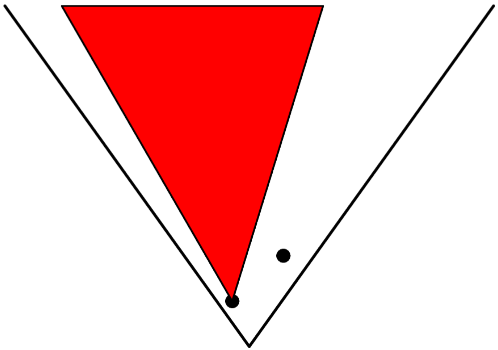

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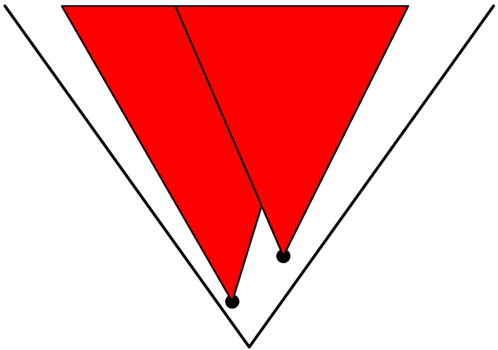

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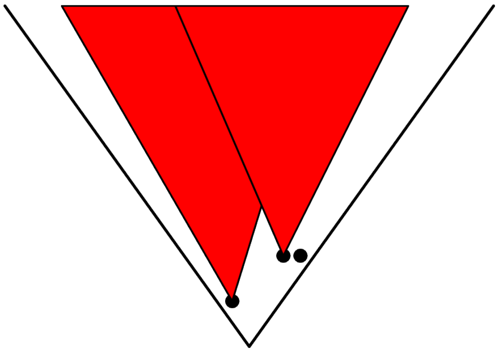

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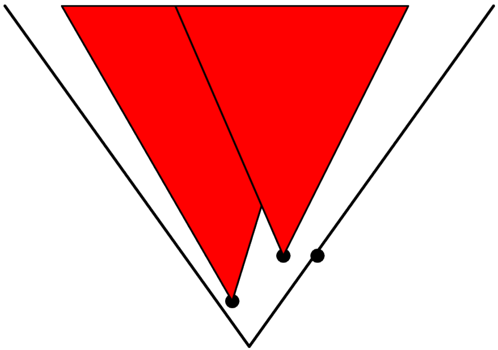


Is this sub-structure in the data sample?

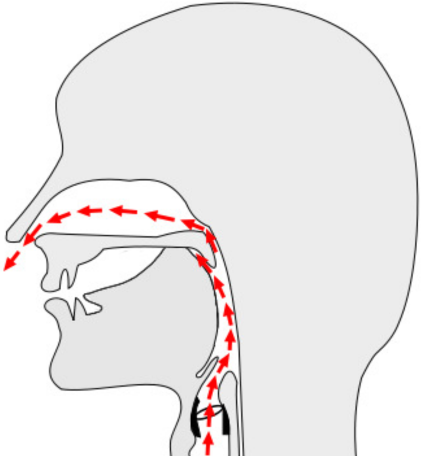
Example: Features in Linguistics

sing

ring

bling

ng = [+Nasal,+Voice,+Velar]



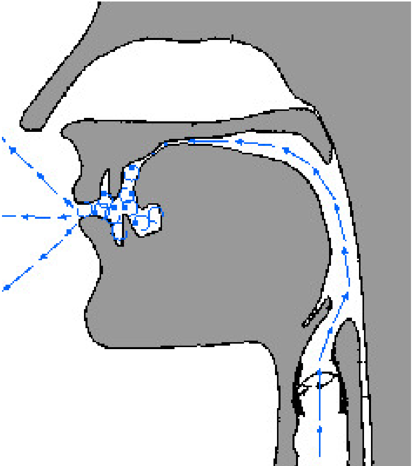
Example: Features in Linguistics

sand

sit

cats

s= [-Nasal,-**Voice**,- **Velar**]

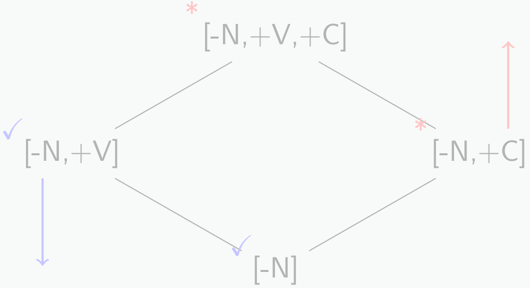


Structuring the Hypothesis Space: Feature Matrix Ideals

Feature Inventory

- $\pm$N = Nasal
- $\pm$V = Voiced
- $\pm$C = Consonant

Example



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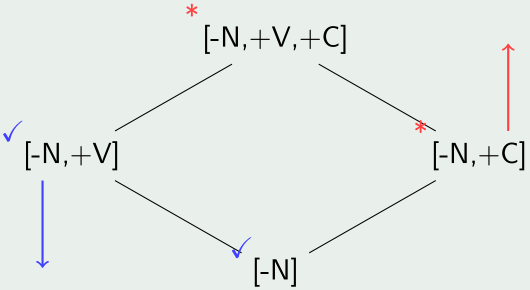
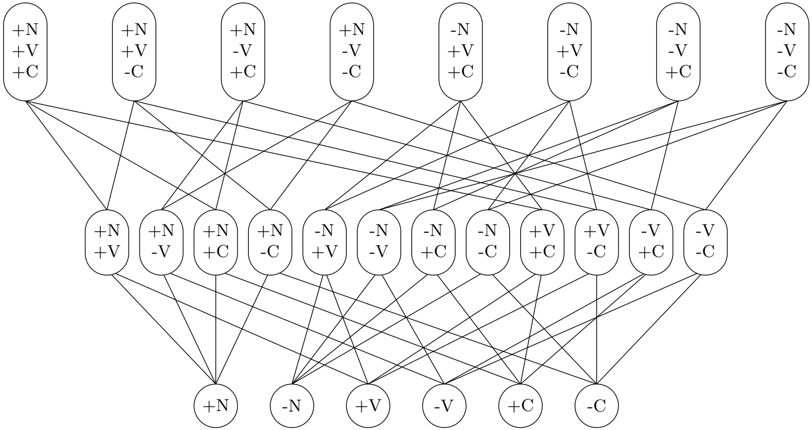
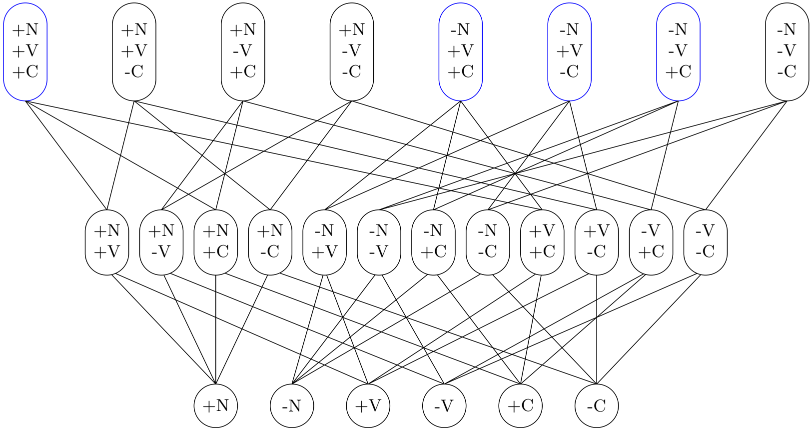


Example



+N +V +C
+N +V -C
+N -V +C
+N -V -C
-N +V +C
-N +V -C
-N -V +C
-N -V -C
+N +V
+N -V
+N +C
+N -C
-N +V
-N -V
-N +C
-N -C
+V +C
+V -C
-V +C
-V -C
+N
-N
+V
-V
+C
-C

Example



+N +V +C
+N +V -C
+N -V +C
+N -V -C
-N +V +C
-N +V -C
-N -V +C
-N -V -C
+N +V
+N -V
+N +C
+N -C
-N +V
-N -V
-N +C
-N -C
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+N
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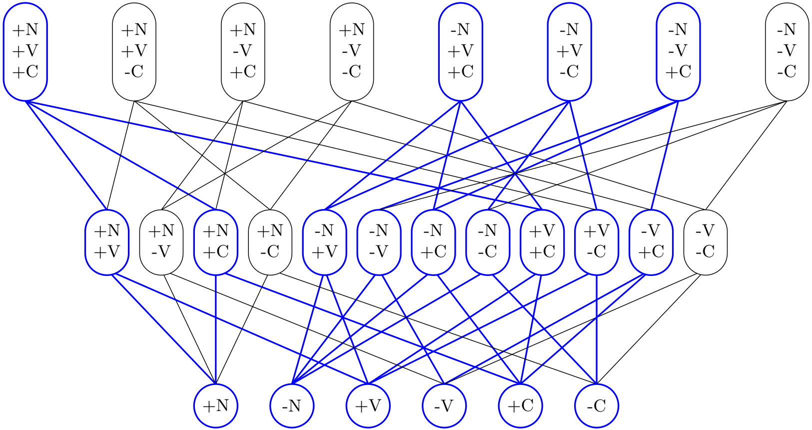
+V
-V
+C
-C

Example



+N +V +C
+N +V -C
+N -V +C
+N -V -C
-N +V +C
-N +V -C
-N -V +C
-N -V -C
+N +V
+N -V
+N +C
+N -C
-N +V
-N -V
-N +C
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+V +C
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-V +C
-V -C
+N
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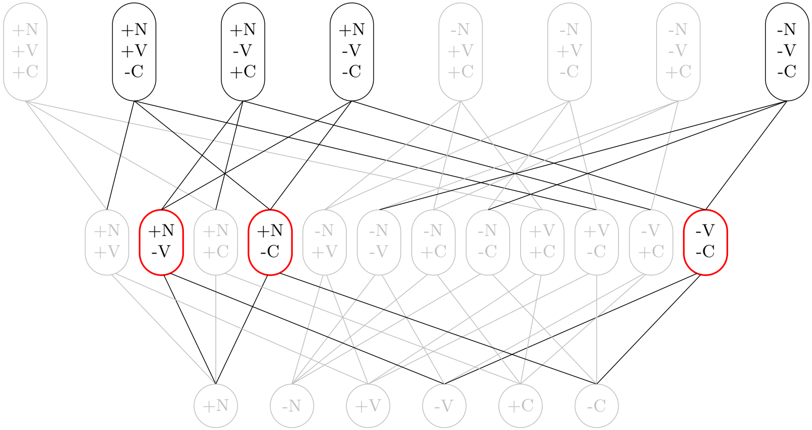
+V
-V
+C
-C

Example



+N +V +C
+N +V -C
+N -V +C
+N -V -C
-N +V +C
-N +V -C
-N -V +C
-N -V -C
+N +V
+N -V
+N +C
+N -C
-N +V
-N -V
-N +C
-N -C
+V +C
+V -C
-V +C
-V -C
+N
-N
+V
-V
+C
-C

Two Ways to Explore the Space

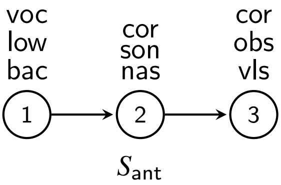
Top-Down Induction

- Start at the most specific points (highest) in the space
- Remove all the substructures that are present in the data.
- Collect the most general substructures remaining.

Bottom-Up Induction

- Beginning at the lowest element in the spave,
- Check whether this structure is present in the input data.
- If so, move up the space, either to a point with an adjacent underspecified segment, or a feature extension of a current segment, and repeat.

Semilattice Explosion



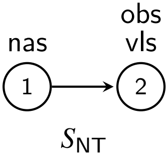
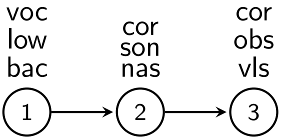


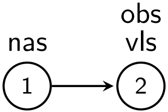
Table 2
Number of possible constraints for various values of $|C|$ and n

		$\lvert C\rvert$			
		30	**100**	**200**	**400**
	1	30	100	200	400
	2	900	10,000	40,000	160,000
n	**3**	27,000	1,000,000	8 million	64 million
	4	810,000	100 million	1.6 billion	26 billion
	5	24 million	10 billion	320 billion	10 trillion

Semilattice Explosion



S_{ant}



S_{NT}

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Plan of the project

What has been done

Provably correct bottom-up learning algorithm

Goals of the Project

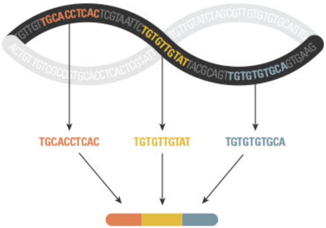
- Model Efficiency
- Model Implementation
- Model Testing - large linguistic datasets
- Model Comparison: UCLA Maximum Entropy Learner

Broader Impacts

- Learner that takes advantage of data sparsity
- applicable on any sequential data (language, genetics, robotic planning, etc.)
- implemented, open-source code

INSTRUCTIONS IN THE CODE

Healthy



DNA
Along with genes (shown here in **orange**, **yellow**, and **blue**), which produce the components for proteins, the genome contains non-coding instructions (**gray**) that direct how these components are assembled.

ASSEMBLY
The cell transcribes specific parts of the code according to the instructions.

PROTEIN
The parts are then assembled into a healthy protein.

Diseased

DNA
A mutation (**red**) in the non-coding instructions causes one gene segment to be ignored.

ASSEMBLY
This variation makes the cell skip over a protein-coding segment of the genome.

PROTEIN
The error in the instruction set leads to an altered protein, which may raise the risk for disease.