Hyperdimensional computing for human data meets the squinting linguist

Jussi Karlgren

Gavagai | KTH | (Currently Visiting Scholar at Stanford)

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- stylistics, genre, statistical models of language in use, distributional semantics
- various industrial research projects
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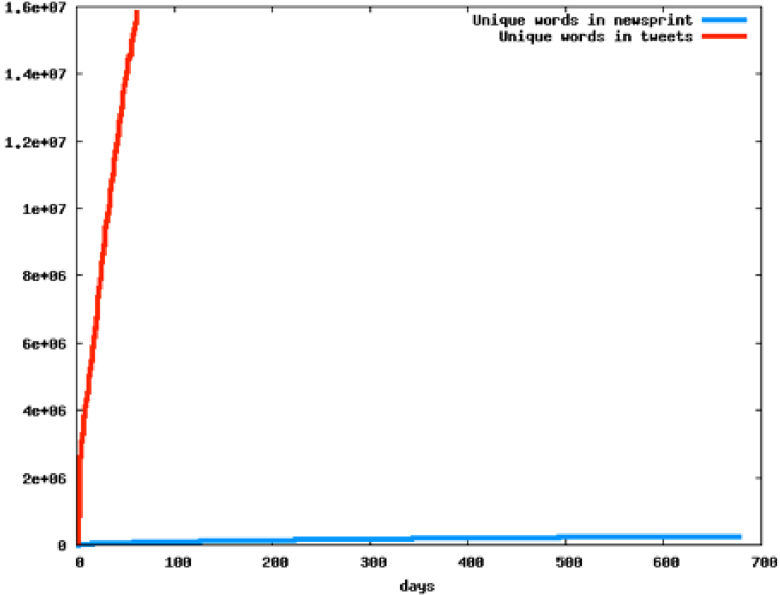
the pattern is more interesting than the data points

- new services, e.g. Internet of Things, sensor networks, human-generated data, universal logging: streaming data from many devices, many people, many levels of abstraction

language is a pilot case for high volume and high variety data



human information processing

- human information processing is effective for streaming data
- handles analogy & saliency
- observes patterns and change rather than the literal
- operates with self-learning rather than instruction

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worth keeping in mind as a model

requirements for a knowledge representation

a representation should:

- have descriptive and explanatory power

  (allow backtracking into observations)
- be practical and convenient for further application

  (retain feature structure)
- be reasonably true to human performance

  (handle streaming and analogy!)
- handle patchy data

  (provide support for generalisation, defaults and constraints)
- be computationally habitable

  (not grow superlinearly with data input)
- be general

  (not tightly bound to some task)

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high-dimensional computing

the approach suggested by us is

- high-dimensional

  to allow a rich representation

- implemented as a vector space

  mathematically well defined and manageable for implementation

- uses random patterns to index observations

  achieves orthogonality for all practical purposes

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distributional semantics

the weather is great in barcelona
the weather is gray in stockholm
the weather is hot in lodi
the climate is passable in nice
the weather is chilly in helsinki
the weather is nippy in moscow
the weather is nice in hong kong
the weather in syktyvkar is balmy
the climate is chilly at the office
the tea is hot
i drink tea
a hot meal will make you feel better
enjoy your hot beverages

- Zellig Harris. 1968. Mathematical structures of language.

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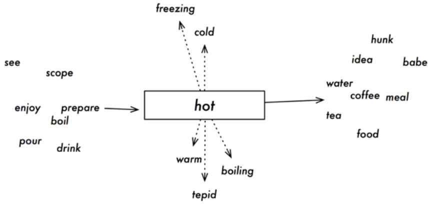

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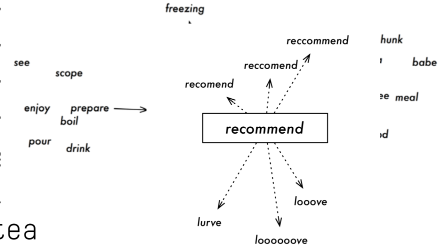

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semantic base technology

- is this an example of that?
- are these two the same?
- has this changed? how?
- what is the relation of this and that?
- is this a new way of saying that?
- are these or those more like this?
- is this typical or strange?
- can we trust this?
- does the author believe this to be true?

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Meaningful application

Semantic layer

Crunch layer

Distributed processing architecture

Database technology or similar

Data stream

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hyperdimensional computing in practice

- random index vectors or labels for basic features
- aggregated context vectors for cooccurrences of features
- similarity between vectors can be measured by cosine
- operations on vectors:
  - addition which yields a similar vector to the inputs
  - multiplication which yields a dissimilar vector to its inputs but preserves relative similarity
  - permutation allows for e.g. sequences or tensors to be represented in one vector
- allows for explicit feature engineering if necessary

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```
   hot  [0, 0, 0, 0, 0, 0]
chilly  [0, 0, 0, 0, 0, 0]
```

```
the weather is hot ... the weather is chilly ...
```

```
weather: [ 0, -1, 0, 1, 0, 0]
```

```
   hot  [0, -1, 0, 1, 0, 0]
chilly  [0, -1, 0, 1, 0, 0]
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the weather is hot … the weather is chilly … the climate is hot … the climate is chilly …

```
weather: [ 0, -1, 0, 1, 0, 0]
climate: [ 1, 0, -1, 0, 0, 0]
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chilly  [1, -1, -1, 1, 0, 0]
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the weather is hot … the weather is chilly … the climate is hot … the climate is chilly …

the weather turned hot … the climate turned chilly …

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weather: [ 0, -1, 0, 1, 0, 0]
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chilly  [1, -2, -1, 2, 0, 0]
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many parameters, but simple experimentation!

- Pentti Kanerva, Jan Kristoferson, and Anders Holst. 2000. Random Indexing of Text Samples for Latent Semantic Analysis. CogSci.
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quantitative characteristics

knowledge representation: features for observations, aggregated into states, allow verification, decomposition, and various calculus operations

a holographic model using random patterns allows vastly larger feature palette given a preset dimensionality of representation

noise loss, twenty items vs random correlation, in 100, 500, 1000, 2000 dimensions

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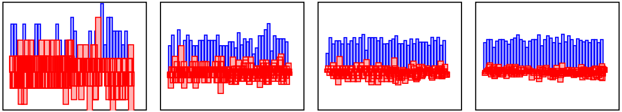

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bridge between theory and use cases

three levels of sophistication for large scale text analysis

1. what are they talking about?
2. how are they talking about it?
3. what are they saying about it?

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implementational challenge

use distributional models for items beyond the immediately topical and referential

- enrich representation beyond token by token analysis
- broaden scope to utterances

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understanding distributional semantics

- many see distributional semantics as something given, as something naïve, and something with little theory

  ("viel data und wenig theorie")

- i am looking for features with both signal and explanatory power to deploy in distributional frameworks

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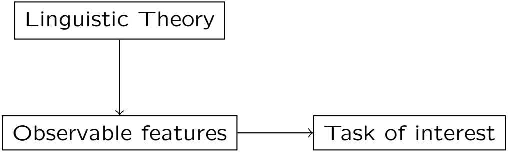

the squinting linguist

Squint!

$$\begin{tikzcd} \boxed{\text{Linguistic Theory}} \arrow[r] \arrow[d] & \boxed{\text{Concepts}} \\ \boxed{\text{Observable features}} \arrow[r] & \boxed{\text{Task of interest}} \end{tikzcd}$$

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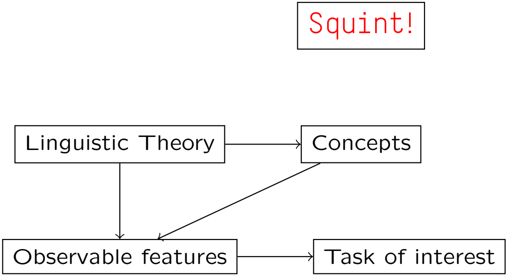

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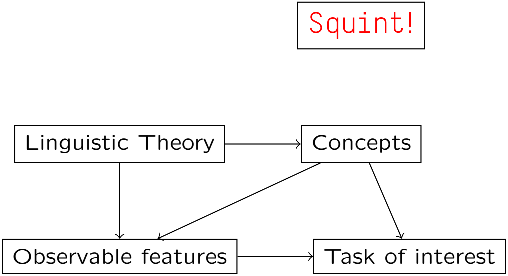

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(a) words

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„I really did not like the clarinet, I am afraid: it sounded weak!”

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find neighbours to:

„I really did not like the clarinet, I am afraid: it sounded weak!"

(a) words:

My sister plays the clarinet.

loads of sentences, represented as sums of features (2000 dimensions; features are 10 non-zero cells):

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(b) constructional elements: negations, amplifiers, …

find neighbours to:

„I really did not like the clarinet, I am afraid: it sounded weak!”

(a) words:
My sister plays the clarinet.

(b) constructions:
I’m surrounded by really soft decadent pillows which do not work for me at all.

loads of sentences, represented as sums of features (2000 dimensions; features are 10 non-zero cells):

(a) words

(b) constructional elements: negations, amplifiers, …

find neighbours to:

„I really did not like the clarinet, I am afraid: it sounded weak!"

(a) words:
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(b) constructions:
I'm surrounded by really soft decadent pillows which do not work for me at all.

in the same representational space. great for hypothesis testing, and for differing tasks!

authorship gender profiling

linguistic theories are not built for this task and are overly specific;
word occurrence models overtrain on topic and do not generalise.

- https://pan.webis.de/clef18/pan18-web/author-profiling.html

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- add all observed features of potential interest into same representation
- use cosine to test which representations fit best
- findings (so far):
  - ♀: first person subjects, „truly"-amplifiers
  - ♂: think verbs and hedges

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why not just use existing models?

- we believe this to be the only sustainable computational approach for knowledge representation in applications where data is streaming, varied, and at real-world scale
- at gavagai we have found no reason to depart from the basic premises for the purpose of processing human language
- this is in contrast to
  - localist representations,
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  - and end-to-end black boxes.

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take home

1.
- handing hypotheses and providing explanatory power are important ...
- ... as is computational habitality ...
- ... neither is optional.

take home

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   - handing hypotheses and providing explanatory power are important ...
   - ... as is computational habitality ...
   - ... neither is optional.
2.
   - feature engineering is a useful method to understand the world ...
   - ... knowledge representations for processing large amounts of data should support it.