Applications

Some applications from the literature

- Text classification Kleyko D, Rahimi A, Rachkovskij DA, Osipov E, Rabaey JM (2018) Classification and recall with binary hyperdimensional computing: tradeoffs in choice of density and mapping characteristics. IEEE Trans Neural Netw Learn Syst 29(12):5880–5898
- Fault detection Kleyko D, Osipov E, Papakonstantinou N, Vyatkin V, Mousavi A (2015) Fault detection in the hyperspace: towards intelligent automation systems. In: 2015 IEEE 13th international conference on industrial informatics (INDIN), pp 1219–1224.
- Analogy mapping Rachkovskij DA, Slipchenko SV (2012) Similarity-based retrieval with structure-sensitive sparse binary distributed representations. Comput Intell 28(1):106–129.
- Reinforcement learning Kleyko D, Osipov E, Gayler RW, Khan AI, Dyer AG (2015) Imitation of honey bees' concept learning processes using Vector Symbolic Architectures. Biol Inspired Cognit Arch 14:57–72
- Kanerva: "high dimensional computing LISP" Kanerva P (2014) Computing with 10,000-bit words. In: 52nd annual Allerton conference on communication, control,and computing (Allerton), pp 304–310
  - Synthesis of finite state automata Osipov E, Kleyko D, Legalov A (2017) Associative synthesis of finite state automata model of a controlled object with hyperdimensional computing. In: IECON 2017—43rd annual conference of the IEEE industrial electronics society, pp 3276–3281
  - Hyperdimensional stack machines Yerxa T, Anderson A, Weiss E (2018) The hyperdimensional stack machine. In: Proceedings of Cognitive Computing, Hannover, pp. 1–2
- Long-short term memory Danihelka I, Wayne G, Uria B, Kalchbrenner N, Graves A (2016) Associative long short-term memory. In: Balcan MF, Weinberger KQ (eds) Proceedings of ICML, PMLR vol 48., New York, pp 1986–1994.
- Predication-based Semantic Indexing (PSI) Widdows D, Cohen T (2015) Reasoning with vectors: a continuous model for fast robust inference. Logic J IGPL/Interest Group Pure Appl Logics 2:141–173
- Jackendoff Challanges of NLP Gayler RW (2003) Vector symbolic architectures answer Jackendoff's challenges for cognitive neuroscience. In: Proc. of ICCS/ASCS Int. Conf. on cognitive science, pp 133–138. Sydney,Australia
- N-gram statistics to recognize the language of a text Joshi A, Halseth JT, Kanerva P (2017) Language geometry using random indexing. In: de Barros JA, Coecke B, Pothos E (eds) Quantum interaction. Springer International Publishing, Cham,pp 265–274
- HTM for mobile robot place recognition Neubert, P., Schubert, S. & Protzel, P. (2019) A neurologically inspired sequence processing model for mobile robot place recognition. In IEEE Robotics and Automation Letters (RA-L) and presentation at IROS.

Application: N-gram statistics to recognize the language of a text

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- Task: Given a text (few sentences) of an foreign language. What is the language?

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  “Il linguaggio, è il complesso definito di suoni, gesti e movimenti attraverso il quale si attiva un processo di comunicazione.“

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  “Un lenguaje (del provenzal lenguatge y del latín lingua) es un sistema de comunicación estructurado para el que existe un contexto de uso y ciertos principios combinatorios formales. Existen contextos tanto naturales como artificiales.”

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  “Taal is in het algemeen elke min of meer complexe vorm van communicatie in de vorm van tekens, die gezamenlijk een systeem vormen. De term kan daarbij betrekking hebben op het systeem als geheel waarvan de tekens de individuele bouwstenen vormen, of op slechts een of enkele van de tekens afzonderlijk.”

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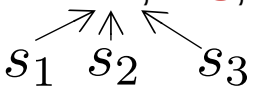

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- Average all N-gram encodings of the text
- Query nearest neighbor from texts with known language

N	Detection success
1	74.9
2	94,0
3	97.3
4	97.8
5	97.3

Joshi et al., 2017

Application: Predication-based Semantic Indexing (PSI)

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- represent “subject–predicate–object” relationships (“aspirin TREATS headache”) using a VSA:

$$S(x) = \sum_{R_j \in \mathcal{R}} \sum_{y \in X} W(R_j, x, y) E(R_j) \otimes E(y) \text{ for all } R_j, y \text{ such that } x R_j y.$$

“semantic” encoding of object — *relations* — *objects* — *random encodings*

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- Introduce a projection-based NOT operator

  S(A) NOT S(B) reduces also similarity to everything similar to S(B)