Schmidt X CARTE A

NLP & Embeddings

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Adapted from material by Charles Ollion & Olivier

Outline

Intro to NLP & Embeddings

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Attention, Transformers and GPT

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Applications of LLMs

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- Combines computational linguistics (e.g. rule-based modelling statistical, ML, and deep learning approaches
- Through NLP, machines can understand, analyze and generate are meaningful and contextually appropriate
- While LLMs have driven an explosion in interest, there are man which paved the way

Common NLP Tasks

- Text Classification, e.g. spam detection
- Named Entity Recognition, e.g. identifying people, places, orga
- Sentiment Analysis, e.g. positive or negative sentiment
- Machine Translation, e.g. Google Translate

Challenges in NLP

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- Nuance: language is full of subtleties and nuances
- Syntax vs Semantics: A phrase can be grammatical but nonsens
  ungrammatical but meaningful

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- They can generate text that is coherent and contextually approp
- They can be fine-tuned for specific tasks

The Encoder-Decoder View o
Learning

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- We will first focus on the encoder part of the model

Embeddings

From Real to Symbolic

- Often, machine learning deals with *real-valued* input: data that
  or can be easily converted to a number and thus contains its ow
- Examples: pixel values in an image, audio samples in a sound fi
  readings
- But what if the input is a symbol?

Symbolic variable

- Text: characters, words, bigrams...
- Recommender Systems: item ids, user ids
- Any categorical descriptor: tags, movie genres, visite
  resume, product categories...

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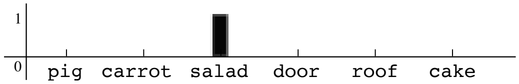
Notation:

$$\text{Symbol } s \text{ in vocabulary } V$$

One-hot representation

$$onehot(\text{'salad'}) = [0, 0, 1, \ldots, 0] \in \{0, 1\}^{|V}$$



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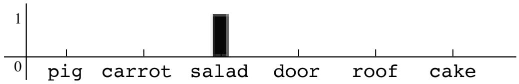

- Sparse, discrete, large dimension $|V|$
- Each axis has a meaning
- Symbols are equidistant from each other:

euclidean distance = $\sqrt{2}$

Embedding

$$embedding(\text{'salad'}) = [3.28, -0.45, \ldots 7.1$$

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- Can represent a huge vocabulary in low dimension, typically: $d \in \{16, 32, \dots, 4096\}$
- Axis have no meaning *a priori*
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Neural Networks compute transformations on continuous vecto

Implementation with Keras

Size of vocabulary $n = |V|$, size of embedding d

```
# input: batch of integers
Embedding(output_dim=d, input_dim=n, input_length=1)
# output: batch of float vectors
```

Implementation with Keras

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$$embedding(x) = onehot(x) . \mathbf{W}$$

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$$embedding(x) = onehot(x).\mathbf{W}$$

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- $\mathbf{W}$ are trainable parameters of the model

Distance and similarity in Em space

Euclidean distance

$d(x, y) = ||x - y||_2$

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Cosine similari

$cosine(x, y) = \frac{x \cdot y}{||x|| \cdot ||}$

- Angle between poi norm
- $cosine(x, y) \in (-$
- Expected cosine si pairs of vectors is (

Visualizing Embeddings

- Visualizing requires a projection in 2 or 3 dimensions
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t-SNE

Visualizing data using t-SNE, L van der Maaten, G Hinton, *The Journal of Machi* 2008

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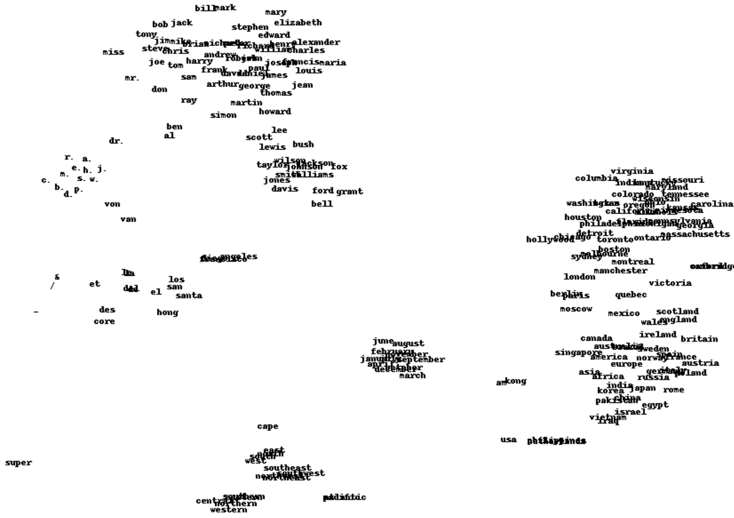
t-SNE projection is non deterministic (depen
initialization)

- Critical parameter: perplexity, usually set to 20, 30
- See http://distill.pub/2016/misread-tsne/

Example word vectors



excerpt from work by J. Turian on a model trained by R. Collobert et al