AMMI Deep Learning DIY:

Day 8

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Natural Language Processing (NLP)

Some applications of NLP

- Why are we interested in Natural Language Processing ?

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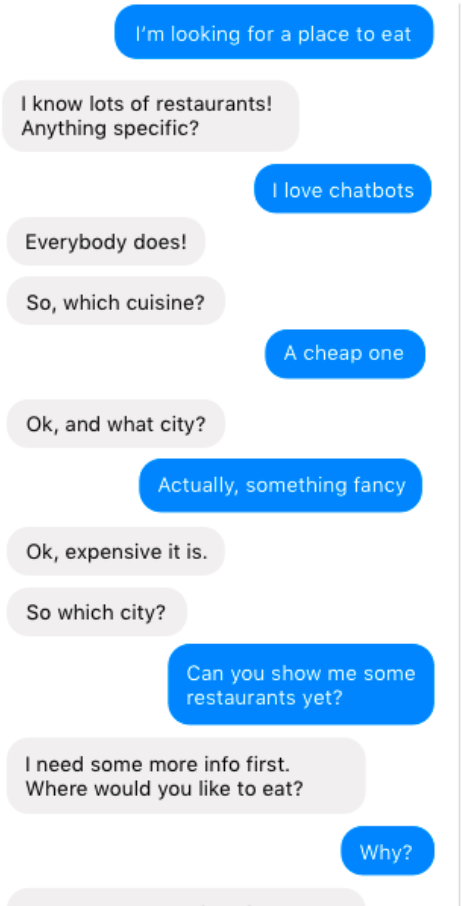
- Conversations & chatbots



Chitchat: Making small-talk or asking questions unrelated to the task

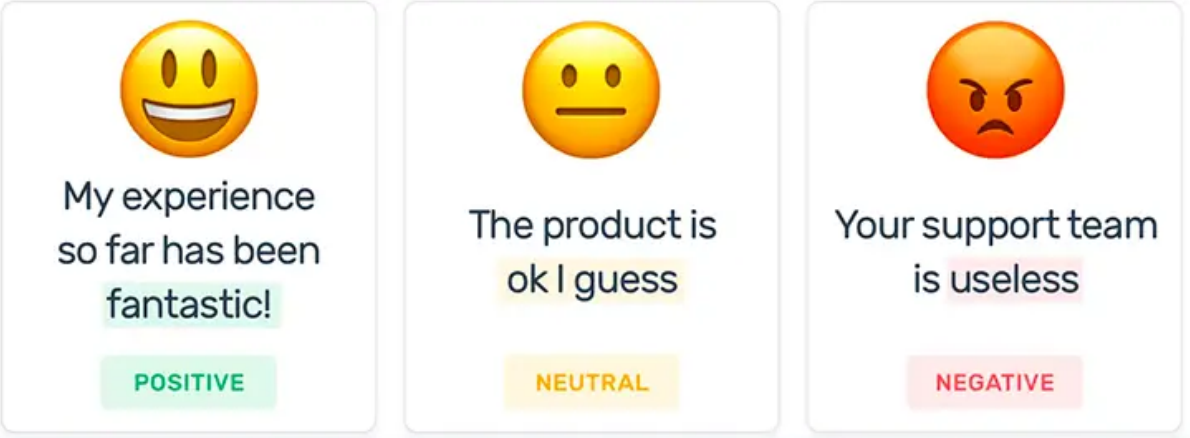
Correction: User has changed their mind about something

Broad context: Questions referring to the broader context of conversation, such as the status of the current task

Narrow context: Questions referring to immediate context, e.g. the most recent system utterance

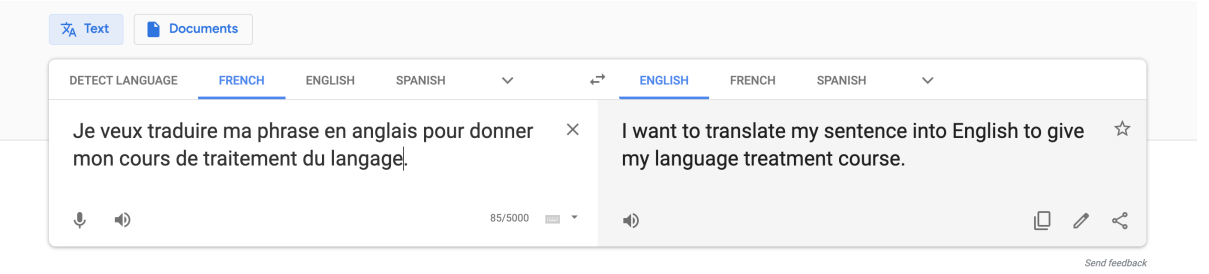
Some applications of NLP

- Why are we interested in Natural Language Processing ?
- Text classification / sentiment analysis



Some applications of NLP

- Why are we interested in Natural Language Processing ?
- Machine translation



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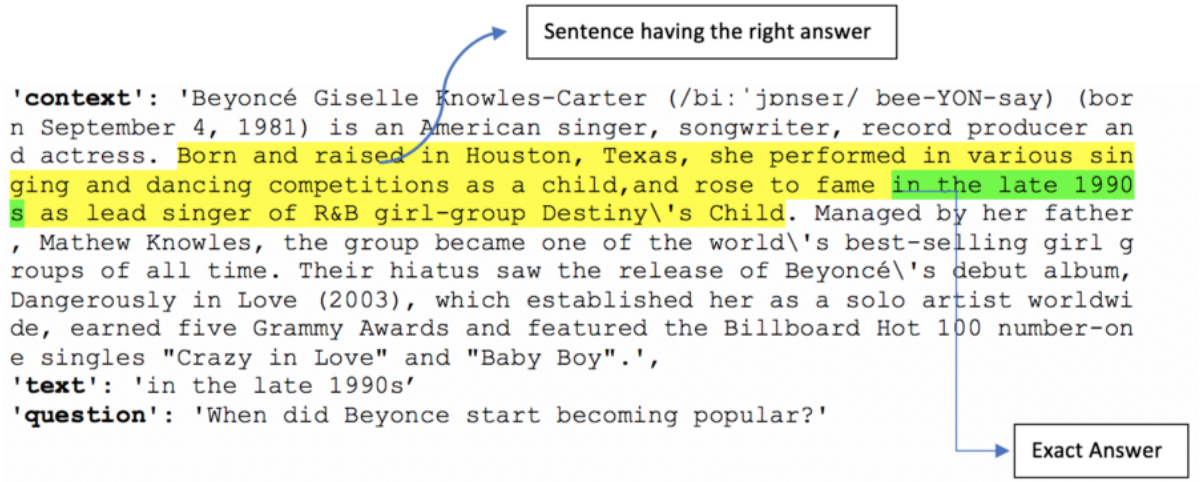

Some applications of NLP

- Why are we interested in Natural Language Processing ?
- +audio: Speech recognition

Some applications of NLP

- Why are we interested in Natural Language Processing ?
- +image: Image captioning

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

Natural Language Processing

1. Word vectors
2. Recurrent models: RNN, LSTM

Word vectors / embeddings

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- Why ?
  - Our machines (linear regression, neural nets) work with vectors (i.e. feature representations)

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3. Transferring to downstream applications
    - text classification / sentiment analysis
    - embedding layers

Learning word vectors

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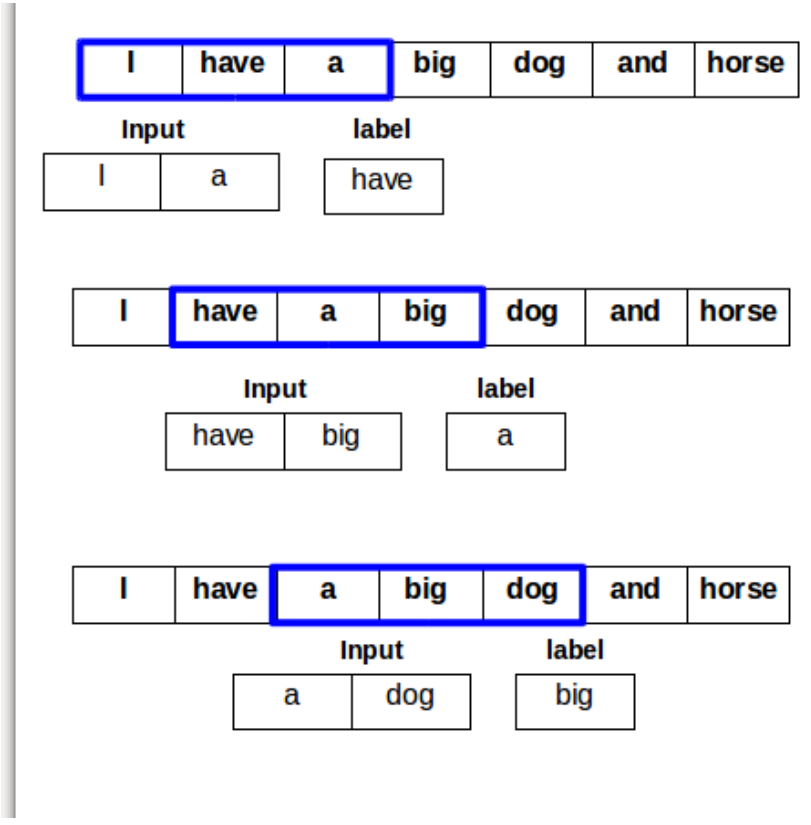
- Given a corpus of text, we predict a word from its context



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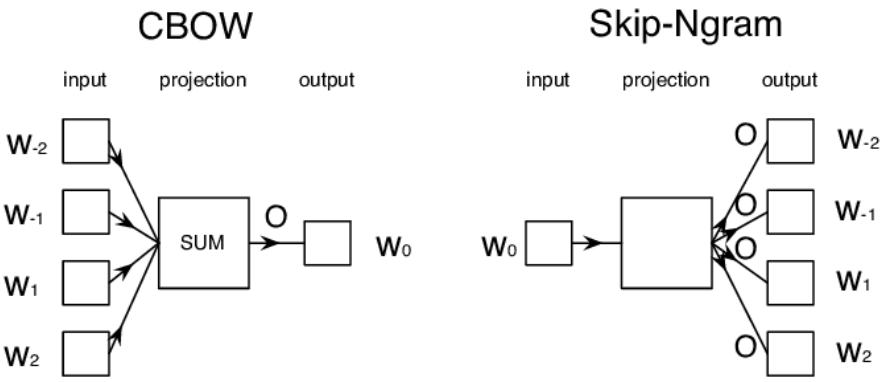
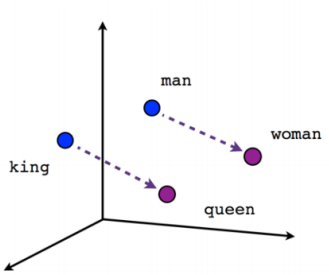
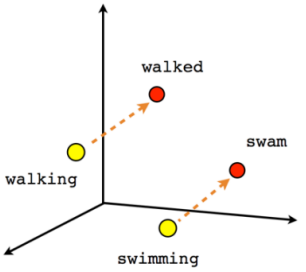


Properties: linear relationships

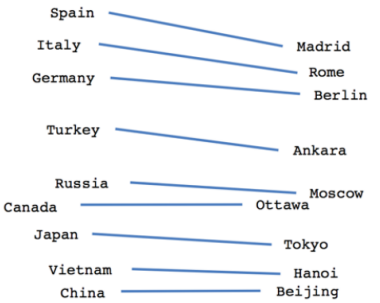
- Linear relationships between words
  - There are "directions" in the learned space
  - ex: country-capital, male-female, etc.



Male-Female



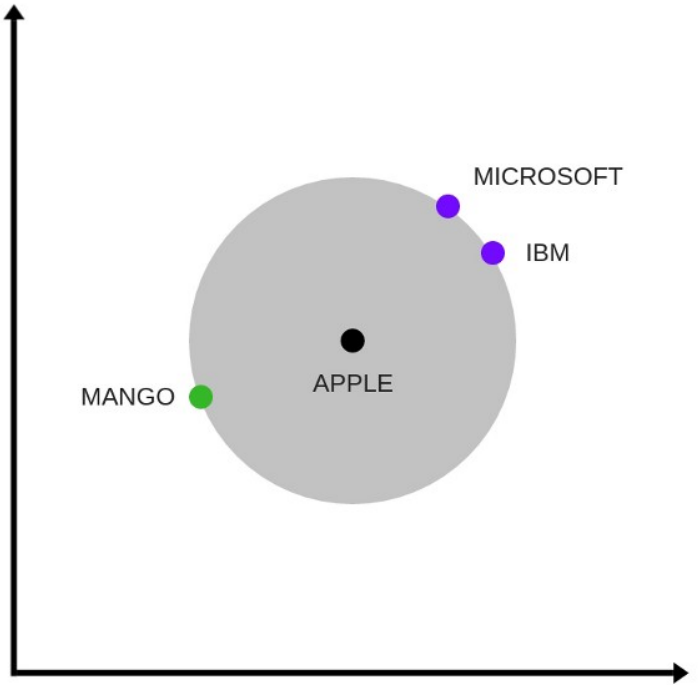
Verb tense



Country-Capital

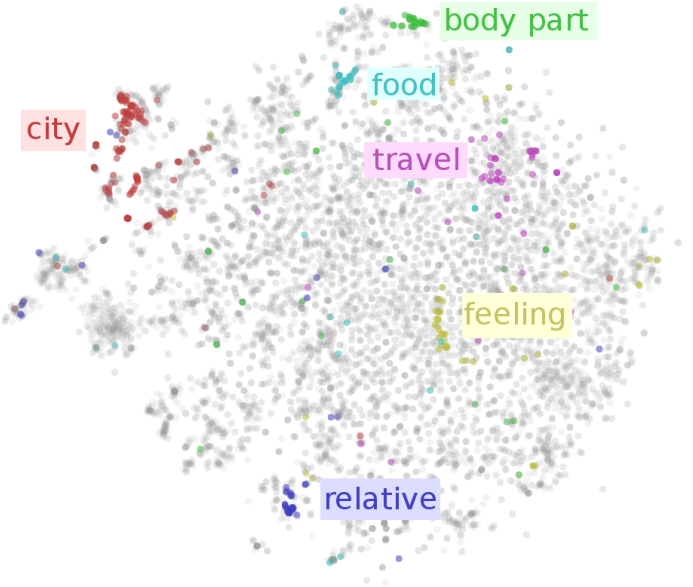
Properties: nearest neighbors

- Nearest neighbors of points are often semantically related



Properties: visualization

- T-SNE plot of word embeddings



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Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

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- This is still an active research topic

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  - Each sentence is the average of all its word embeddings
  - We train a simple linear model on top of it

Transfer: embedding layer

- Word vectors can be used as the first layer in a neural network
- More on that later

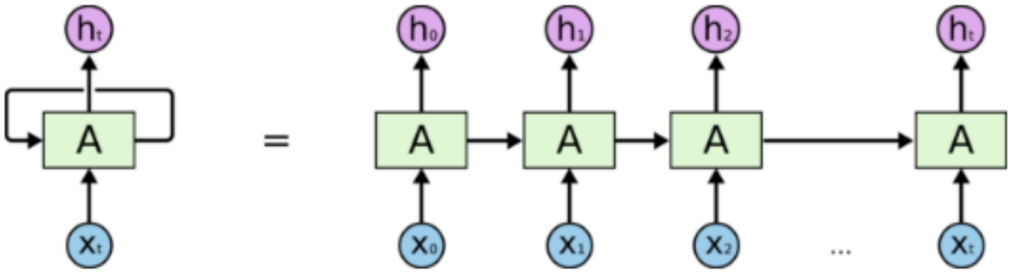
Recurrent neural networks

- Main idea: we predict the next word in a sentence from the current word and the past
- The past is represented by a hidden state $_{-1}$
- The current word is and its embedding is
- We compute the current state by the equation:

$$h_t = \sigma(Ah_{t-1} + Bx_t)$$

- We predict the next word using

Recurrent neural networks



An unrolled recurrent neural network.

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  - It has a simple solution: gradient clipping
  - If the norm of the gradient is higher than some threshold, we rescale it