Consolidation week
Word Embeddings and End-to-end NLP

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Outline

- Semantics
- Word embeddings
  - Count based
  - Word2vec
  - Elmo
- Compositionality and end-to-end

Mid-term exam

- Takes place on Monday (26th) in the lab session
- 10 multiple choice questions
- Cover weeks 1-5
- 20% of the final grade

Textbooks and materials for next few weeks

- Some parts of Speech and Language Processing
- Natural Language Processing with transformers (https://transformersbook.com/)
- Individual journal articles and conference papers

Semantics

What do the words mean?

- What does “A blue cat sat on the red mat” mean?
- What does “cat” mean?
- What does “a blue cat” mean?
- What does “the blue cat” mean?
- Now consider the sentence “Joanna sat on the red mat?”
  - What does “Joanna” mean?
  - Does the meaning change for someone who knows her compared with someone who doesn’t?

Some concepts of semantics

- The meaning of a linguistic unit can be
  - A list of properties (small, carnivore, four legged, has fur)
  - A set of all entities that contain said properties (“A cat” can refer to any and all cats)
  - An abstract concept: some undetermined cat performing the act of sitting
  - A concrete and determined entity (Simon’s cat, your friend Joanna)
  - A set of other related entities (e.g., a “cat” is a type of “animal”)
- And humans still manage to talk to and understand each other, talk about concepts they have never seen or entities that don’t exist (e.g., unicorns)

But wait! There is more

- How to go from the meaning of [“a blue cat”, “sat”, “on the red mat”] to a single meaning?
- What does “a blue cat sat on the red mat” mean?
  - It is not a cat, or a mat, or the color blue
  - It could be truth or a lie. Perhaps a blue cat has never sat on a red mat. Or blue cats don’t exist

What we have learned so far

- Semantics is the study of meaning
- How to represent meaning for algorithms?
- Do we need full theory of meaning?
    - Goal oriented representations

Pop quiz

- Which of the following are meaning representations
  - Part-of-speech tag
  - Word2vec
  - Syntactic tree
  - Tf-idf vector
  - ELMO
  - Wordnet synset

Vector representations and word embeddings

The distributional hypothesis and word embeddings

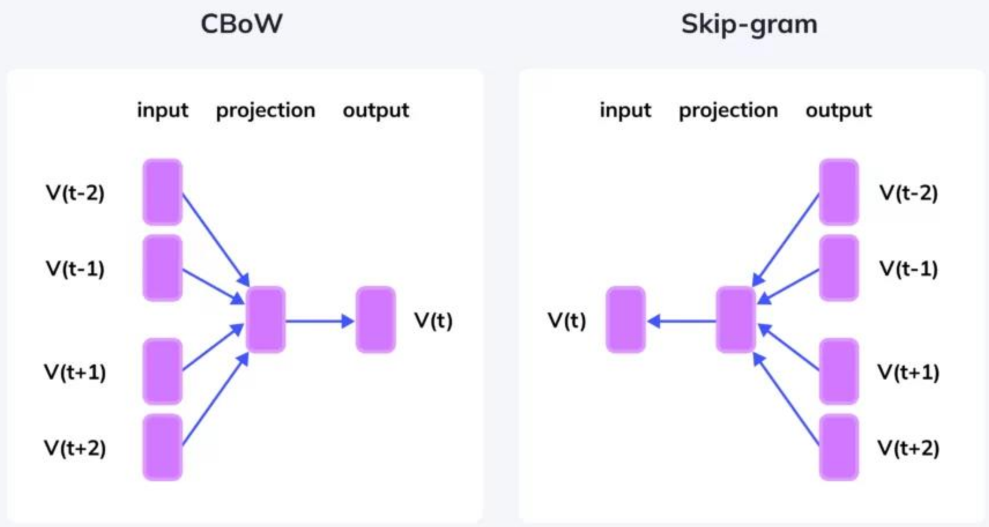
- The distributional hypothesis
  - What does it state?
  - How does it affect NLP?
- Word embeddings
  - Encoding words as “semantic” vectors

Count based vector representations

- Obtain a large corpus in the language/domain of interest
- Define a context of co-occurrence
  - What contexts can you think of?
- Count and fill in a co-occurrence matrix
- Apply transformations (which?)

Word2Vec

- Learning embeddings directly from text
- A simple neural architecture
- Two algorithms
  - What is the difference between them?



Pop Quiz

- Negative sampling is used to:
  - Improve fairness in classifiers
  - Process negation in text
  - Improve computational efficiency
  - Create dictionaries of negation
  - Reduce the effect of positive sampling

Negative Sampling

- Global objective: maximize the log probability of the dataset of size T with a context size c

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0} \log p(w_{t+j}|w_t)$$

- Calculate the probability of every word given context (or the other way around)

$$p(w_O|w_I) = \frac{\exp({v'_{w_O}}^T v_{w_I})}{\sum_{w=1}^{W} \exp\left({v'_w}^T v_{w_I}\right)}$$

- Training with a softmax over the whole vocabulary is expensive

- Convert the task into "classifying the correct objective" using a logistic

$$P(+|w,c) \;=\; \sigma(\mathbf{c}\cdot\mathbf{w}) = \frac{1}{1+\exp\left(-\mathbf{c}\cdot\mathbf{w}\right)}$$

Calculating similarity

- How do we calculate similarity between vectors?

- Dot product

$$\text{dot product}(\mathbf{v}, \mathbf{w}) = \mathbf{v} \cdot \mathbf{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

- Cosine

$$\text{cosine}(\mathbf{v}, \mathbf{w}) = \frac{\mathbf{v} \cdot \mathbf{w}}{|\mathbf{v}||\mathbf{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

Difference between count-based vectors and w2v

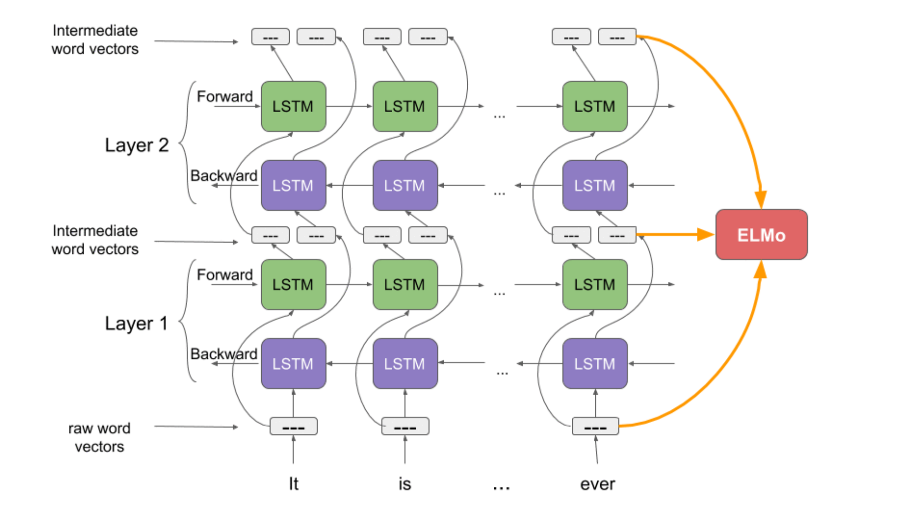
- Are count based vectors word embeddings?
- Are tf-idf vectors word embeddings?
- Can you list some differences between count-based vectors and word embeddings?

ELMO

- What is the most important difference between ELMO and word2vec?

- What makes ELMO representations “deep”?

- What is the training objective behind ELMO?



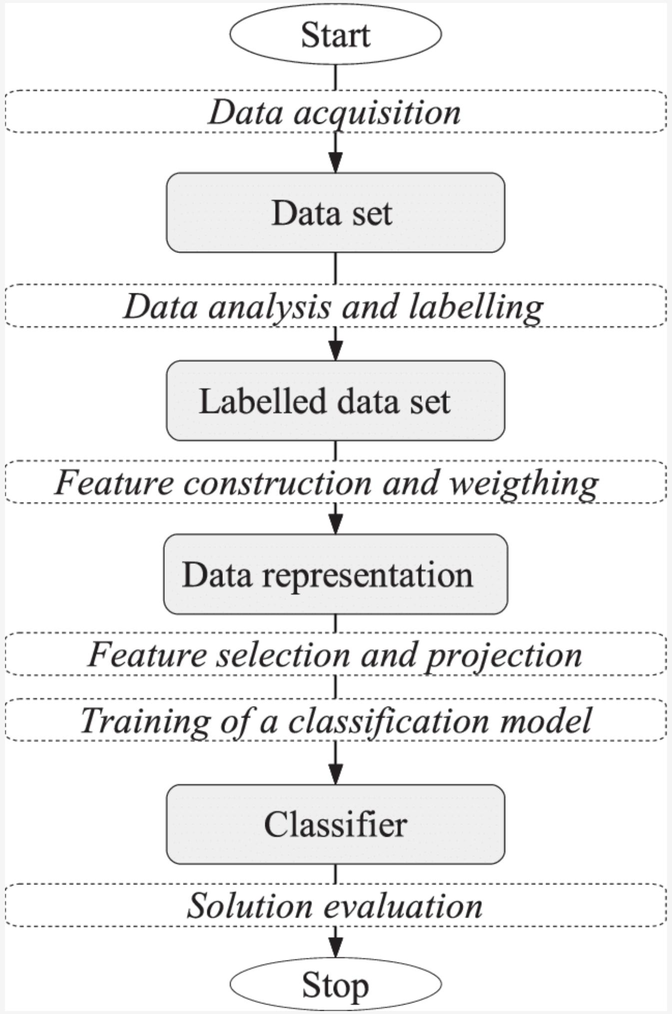
Compositionality and End-to-end

Feature engineering

- Analyze the problem, the input, and the desired outcome
- Explore existing resources and processing techniques
- Select the most relevant features and feature-extraction methods
- Empirically test what works best

Text classification using features

- Step by step process
- Involves active human engagement
  - Feature selection and extraction
- Data is fed into a classifier (Logistic, NB, SVM)
- Iteratively improve feature selection and model (hyper) parameters



Why not go end to end?

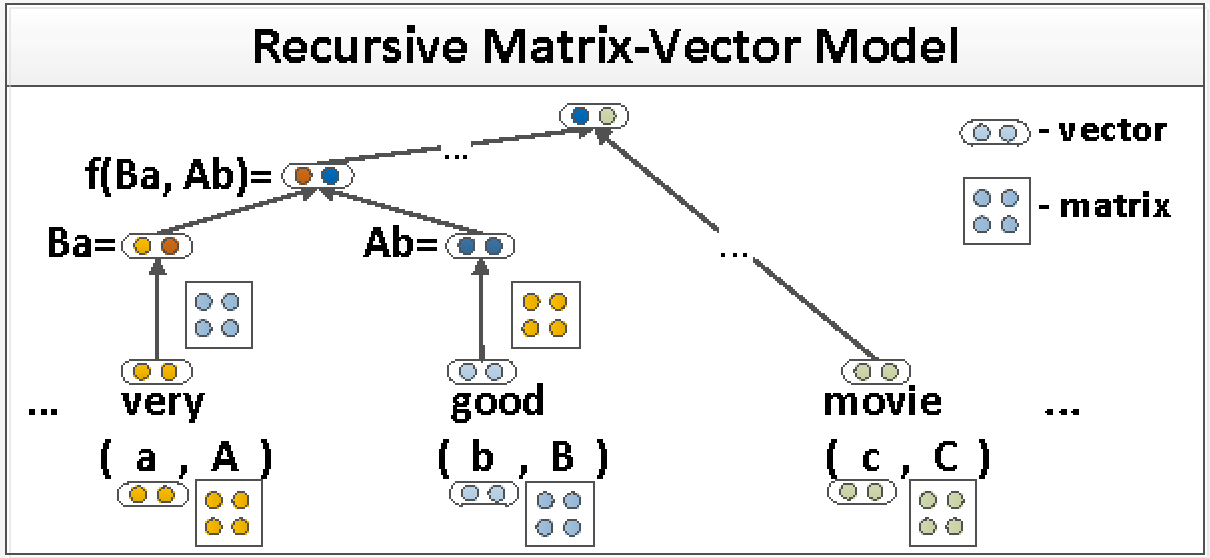
- Do we need full pipelines?
- Embeddings make it possible to “feed” text directly into models
- Is it possible to go fully end-to-end and eliminate
  - Accumulation of errors
  - Human labor and supervision
  - (In)compatibility issues between elements?

Embeddings and the problem of compositionality

- Embeddings represent individual words
- NLP deals with processing texts
- How to go from word representations to text representations?
    - Can you list different compositional approaches?

Vector operations

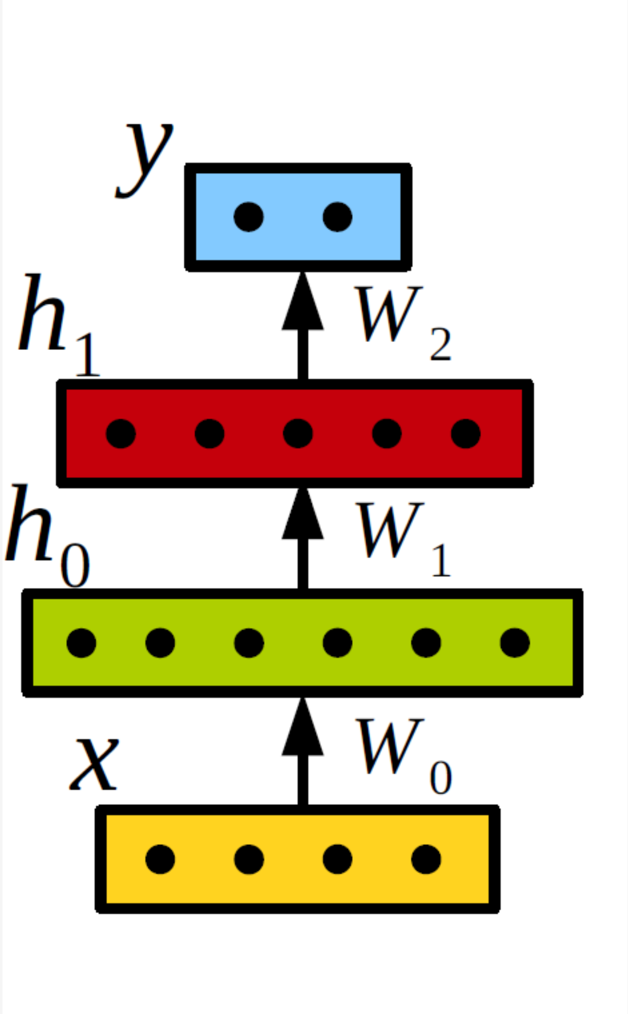
- Vector addition
- Pointwise vector multiplication
- Vector concatenation
- Complex matrix-vector operations
- Which of these operations consider text structure?



Compositionality using neural networks

- Convert words into word vectors
- Let the neural network learn compositionality
- What architectures have we discussed?
- What determines the “weights” of the compositionality?

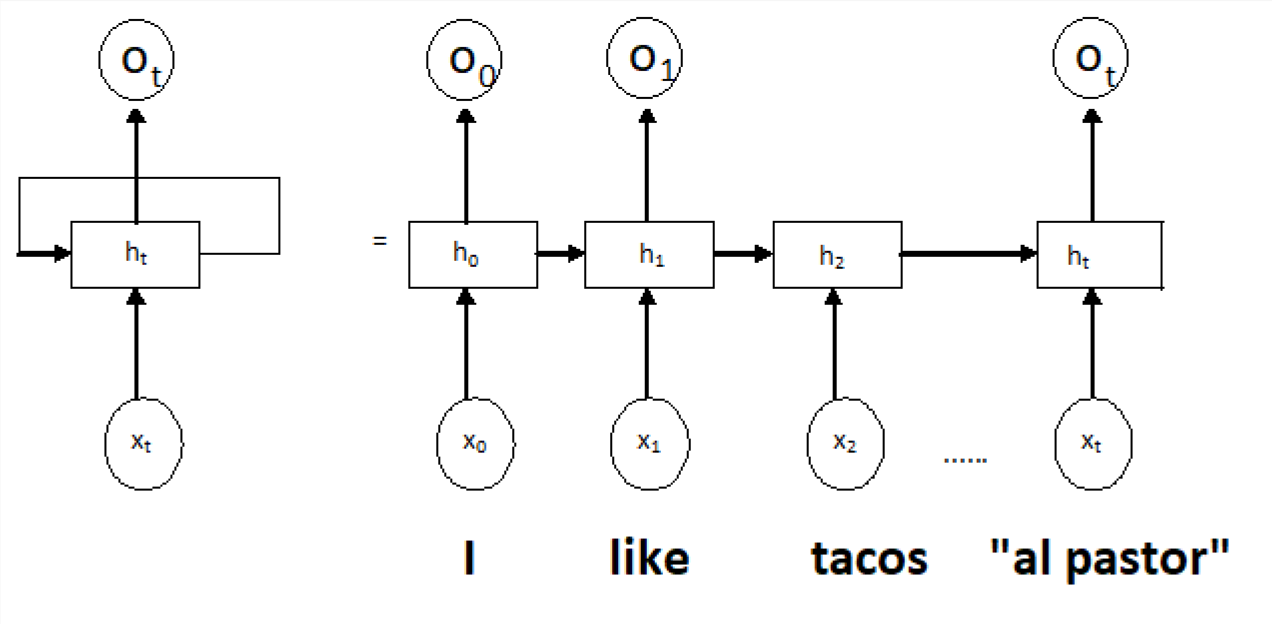
Multi-layer perceptron



- $y = \mathrm{softmax}(h_1 \cdot W_2 + b_2)$
- $h_1 = f(h_0 \cdot W_1 + b_1)$
- $h_0 = f(x \cdot W_0 + b_0)$
- Non-linear functions f:
  - Sigmoid: $\sigma(x) = \frac{1}{\exp(-x)}$
  - Hyperbolic: $\tanh(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)}$
  - ReLU: $\mathrm{rect}(x) = \max(0, x)$

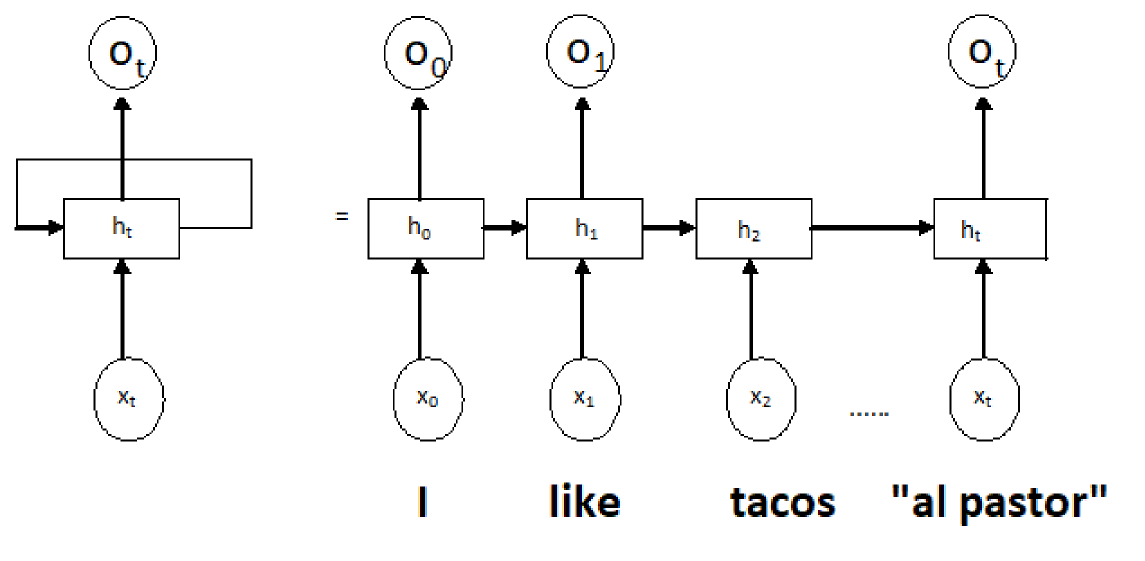
Recurrent neural networks

- How to represent text of varying length?
- Copy the network for each word
- At each timestep t, input is X_t and $h_{(t-1)}$
- I + like + tacos + “al pastor”
- Left to right, combining words one at a time
- Sequence classification
- Sequence to sequence



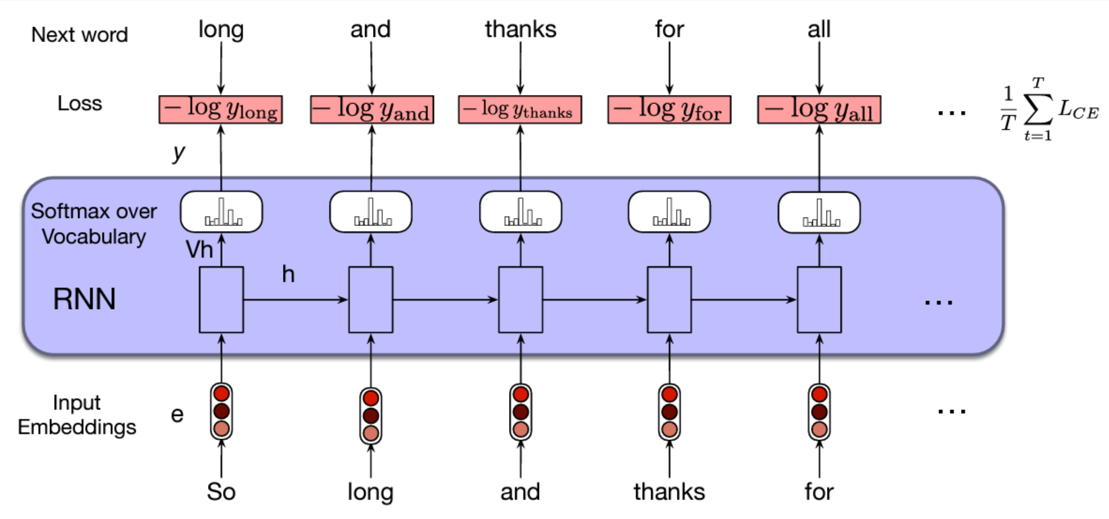
RNNs (formally)

- At each timestep
  - Input x_t, and previous hidden state $h_{(t-1)}$
  - Three sets of weights:
    - input (W_x), hidden (W_h) , and output (W_o)
  - $h_t = f_h(W_x x_t + W_h h_{(t-1)})$
  - $O_t = f_o(W_o h_t)$
  - $J_t = f(O_t, y_t)$
- Pop-quiz: What are we predicting at O?



Neural language modeling with RNNs

- More formally:
  - $h_t = \tanh(W_x x_t + W_h h_{(t-1)})$
  - $\hat{y}_t = \mathrm{softmax}(W_y h_t)$
  - $J_t = -\log \hat{y}_{t,\ \text{correct}}$ (- log prob the word at t+1)



- $J_{sent} = \frac{1}{T}\sum_{t=1}^{T} -log\ \hat{y}_{t,\ \text{correct}}$

- Pop quiz: What is “weight tying” in RNNs?

Figure 9.6 from SLP, chapter 9

Stacked and bidirectional RNNs

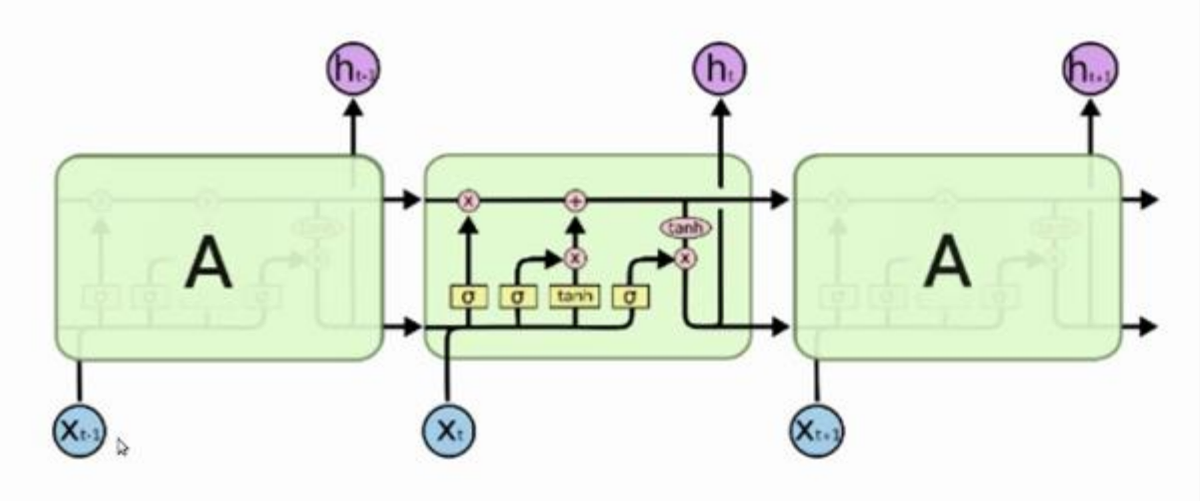
- The basic RNN is a powerful tool
- We can go deeper
- Stacking RNNs
- Bidirectional RNNs

LSTM

- Popular variation of RNN that address native limitations
- Same recurrent concept (copy the network)
- Three different “gates”:
  - Forget gate
  - Input gate
  - Output gate
- Gates manipulate the flow of information through time
  - Addressing conflicting objectives

Understanding the gates

- All gates have the same format:
  - A feedforward layer followed by a sigmoid
- The gates are filtering out information at a certain part of the network
- Each gate has two important aspects:
  - How to calculate the filter
  - What is the input that the filter is applied to
- Pop quiz: which memory we use to calculate gates?

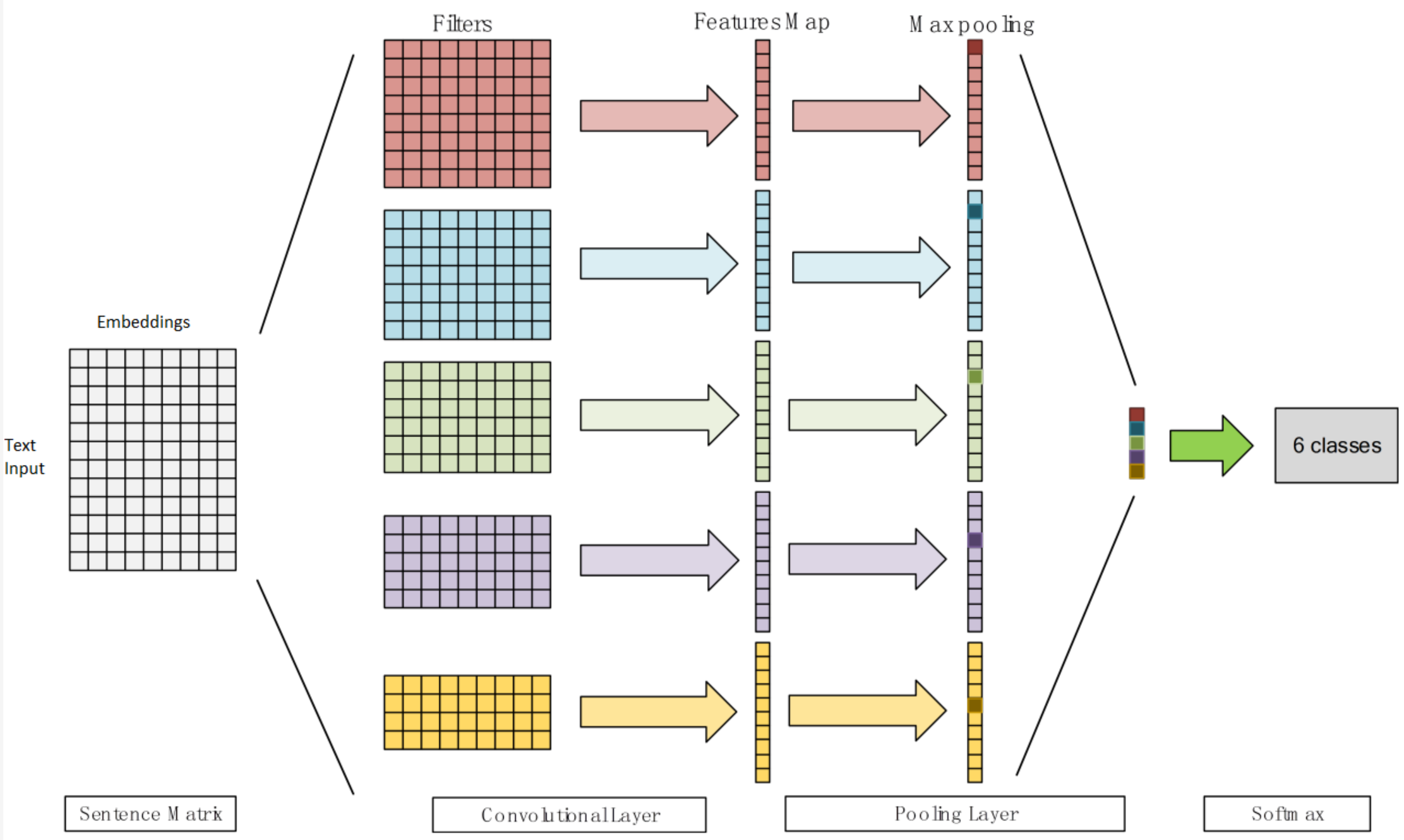


What we have learned so far

Convolutional neural networks (CNN)

- Another popular architecture for NLP
  - Deals with text of various size
- Inspired by computer vision success
- Applying filters of different size to the input (2,3,4) + pooling
  - Analogous to n-grams

Convolutional neural networks (CNN)



Pop quiz: input size

- Can each of these architecture process text of infinite size
  - RNN
  - MLP
  - CNN
  - LSTM
  - Bi-LSTM

Compositionality

- How each network “composes” meaning
  - Feed-forward network
    - Linear combination of words (no order) + activation function
  - RNN/LSTM
    - Recursively, word by word (linear order)
  - CNN
    - Locally, similar to n-gram (proximity window, limited order importance)

Multimodality and multilinguality

- Embeddings and multilinguality
  - Words of any language can be mapped to vectors
  - Words of different languages can be mapped to the same space
  - Mapping and similarity across languuages
- Embeddings and multimodality
  - Images, sound, and other modalities can also be mapped to vectors (e.g., using CNNs)
  - Shared multimodal spaces (vision + language)

The first "should I worry about my job"

- Rapid change in technologies can be stressful

- Three "major" milestones in NLP in the past 10 years
  - Word2Vec and end-to-end models (BiLSTM, CNN) – 2013
  - BERT (and the transformer family) – 2018
  - Large generative language models (GPT3, ChatGPT, Bard) – 2022 - 2023

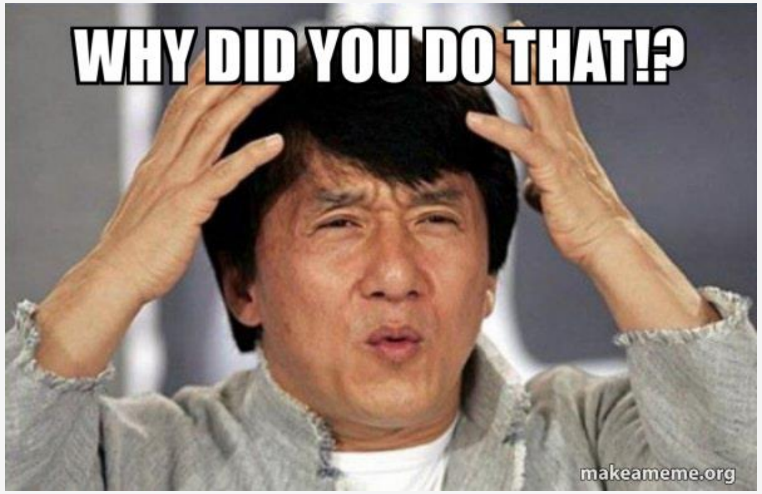
- There are still many unsolved problems

Some concerns

Explainability and Interpretability

- Interpreting feature-based models
    - Feature values (“v1agra”) + weights = prediction (“spam”)

- Interpreting end-to-end neural networks
    - Feature values (300d dense vector)
    - weights (input, forget, output gates)
    - different types of nonlinearity



Explainability and Interpretability

- Why did you do that?
- How did you do that? What makes you say that?
- How can I verify your results?

Bias, Guarantees, and Robustness

- Does the algorithm discriminate?
- Does the algorithm contain bias with respect to race, gender, religion, sexual orientation?
- Does the algorithm guarantee consistent and robust performance?
- Is the algorithm secure from adversarial attacks?

New fields of study in NLP in the are of deep learning

- Explainability of neural networks
- Algorithmic fairness
- Evaluation, unit testing, and adversarial attacks for NLP
- Data centric AI

Conclusions

Embeddings in NLP

- Embeddings changed the way we do NLP
- Valuable stand-alone resource
  - Can be used to query lexical information
  - Can be used as automatically extracted features
  - Can be used for a simple text representation
  - Static and dynamic embeddings, polisemy
- Enable end-to-end neural models

End-to-end neural models

- Minimizing human interaction and supervision
  - Remove the need of feature engineering
  - Only require labeled data for classification tasks
- Improving efficiency and removing accumulation of errors in pipeline
- Enabling full training without depending on external resources

End-to-end neural models

- Introducing new challenges and problems
  - Increased computational complexity
  - Need for more data
  - Error accumulation becomes internal
  - Difficult to interpret and debug
  - Potentially containing biases
  - Ultimately re-invent many of the pipeline parts during training