



# Applications

ADVANCED ARTIFICIAL INTELLIGENCE  
JUCHEOL MOON

1

## Neural Language Models

- NLMs are a class of language model designed to overcome the curse of dimensionality problem for modeling natural language sequences by using a distributed representation of words

one-hot-vector representation of 1B words of bag  
 $\text{dog} \Rightarrow [0 \ 0 \ \dots \ 0 \ 1 \ 0 \ 0 \ \dots \ 0]^T$   
 $\text{cat} \Rightarrow [0 \ 0 \ \dots \ 0 \ 0 \ 1 \ \dots \ 0]^T$   
1,000,000,000

- Neural language models share statistical strength between one word (and its context) and other similar words and contexts

2

2

# The distributed representation

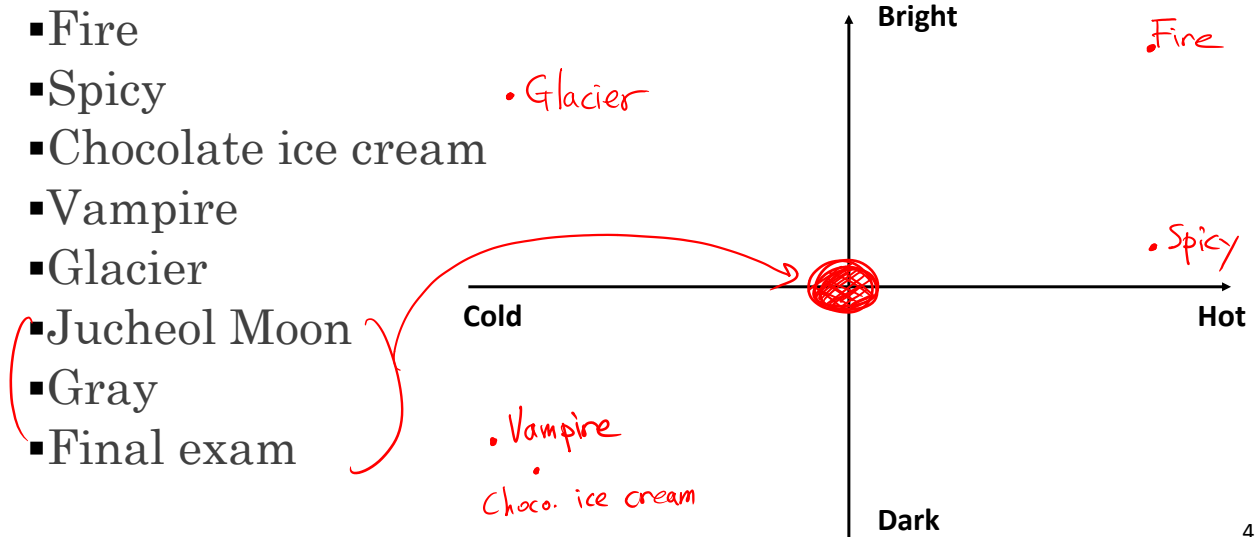
- The language model learns to treat words that have features in common similarly
  - GRE Analogies
    - ADULT : CHILD ::
      - (A) horse : mare
      - (B) cat : kitten
      - (C) swine : sow
      - (D) human : animal
      - (E) cow : herd
  - ENVELOPE : LETTER ::
    - (A) scarf : hat
    - (B) box : bag
    - (C) crate : produce
    - (D) neck : head
    - (E) blood : heart
  - OVERDOSE : PRESCRIPTION ::
    - (A) deprivation : materialism
    - (B) indiscretion : convention
    - (C) affliction : sympathy
    - (D) adventure : expedition
    - (E) drug : medicine

3

3

# Word Embeddings

- Can we locate the words by their characteristics?

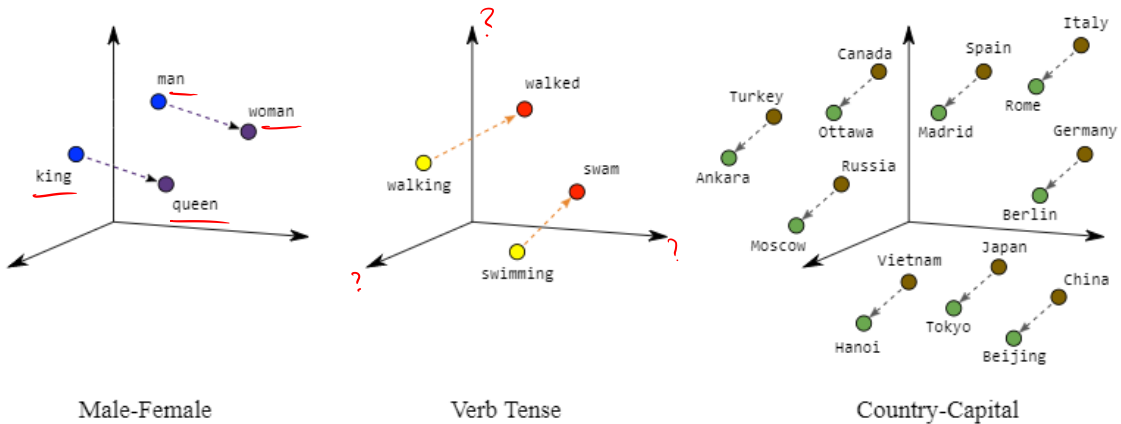


4

4

# Word Embeddings

- In the embedding space, words that frequently appear in similar contexts (or any pair of words sharing some “features” learned by the model) are close to each other.

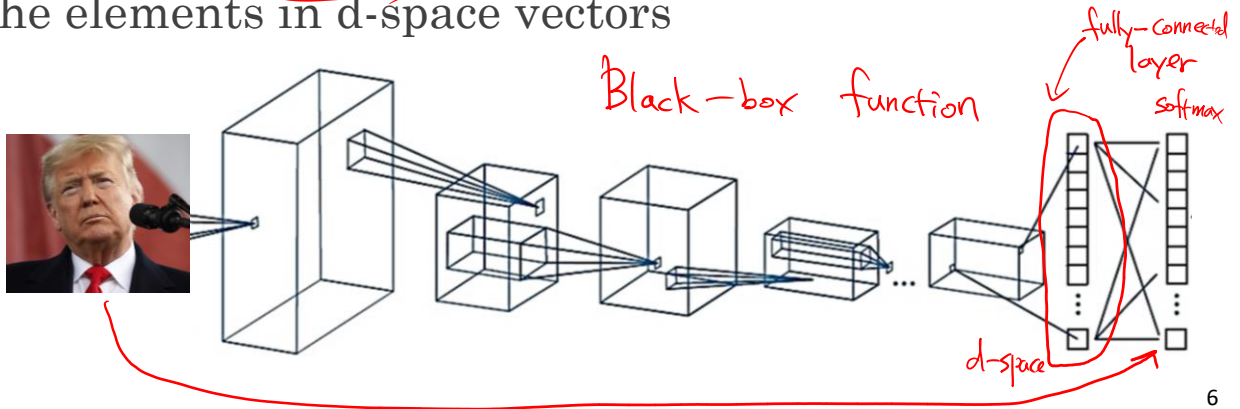


5

5

## Embedding in Vision

- A hidden layer of a convolutional network provides an “image embedding” in d-space
- We (could / could not) interpret the characteristics of the elements in d-space vectors



6

6

# Word Embedding

- Assume we are using word embedding vectors in  $d$ -space

$$\begin{aligned} \text{how} &\rightarrow e_{\text{how}} = [0.1 \quad -0.3 \quad 0.9 \quad \dots]^T \\ \text{are} &\rightarrow e_{\text{are}} = [0.4 \quad 0.1 \quad -0.7 \quad \dots]^T \\ \text{you} &\rightarrow e_{\text{you}} = [0.01 \quad 0.2 \quad -0.3 \quad \dots]^T \end{aligned}$$

$e_{\text{comment}} \quad e_{\text{allez}} \quad e_{\text{vous}}$

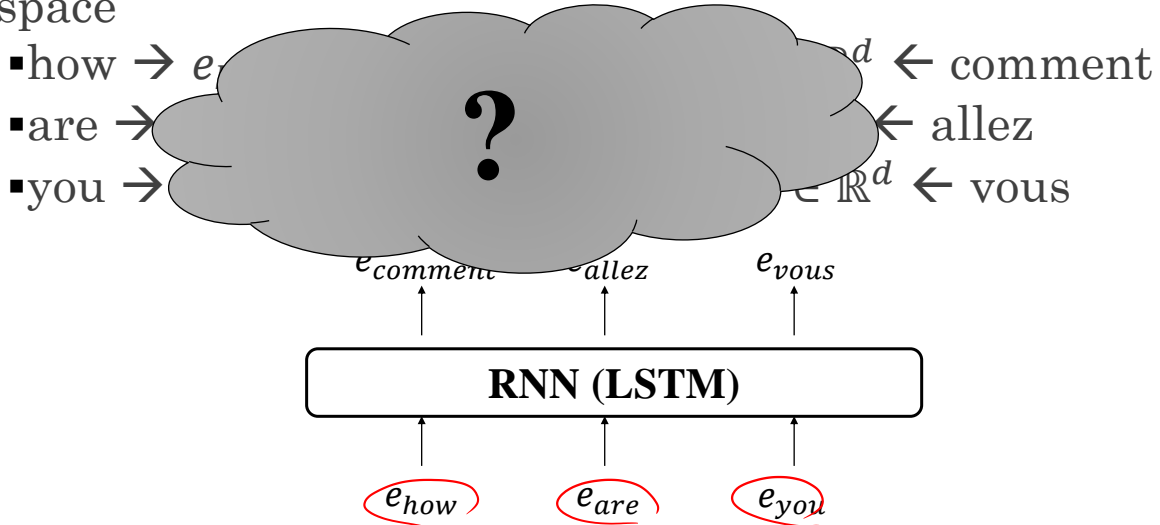
$$e_{\text{how}} \quad e_{\text{are}} \quad e_{\text{you}}$$

7

7

# Word Embedding

- Assume we are using word embedding vectors in  $d$ -space



8

8

## n-grams

- The earliest successful language models were based on models of fixed-length sequences of tokens called n-grams. An n-gram is a sequence of n tokens.
- Ex) Can we predict the blanks?
  - The cat is walking in the bedroom
  - A dog was running in a room
  - The cat is running in a room
  - A dog is walking in a bedroom
  - The dog was walking in the room

9

9

## 3-grams Learning

- Initially, (as usual) set the values of embedding vectors randomly
- Train the values with samples
- Transfer learning is useful

The cat is walking in the bedroom  
A dog was running in a room  
The cat is running in a room  
A dog is walking in a bedroom  
The dog was walking in the room

LSTM

The cat is (walking in the) ~~bedroom~~  
A dog was (running in a) ~~room~~  
The cat is (running in a) ~~room~~  
A dog is (walking in a) ~~bedroom~~  
The dog was (walking in the) ~~room~~

10

10

# Negative sampling

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- Training data set includes only positive samples
  - The cat is **walking in the** bedroom.
  - The dog was **walking in the** room.
- We need to have negative samples
  - The cat is **walking in the** drawer.
  - The dog was **walking in the** fridge.
- Total number of negative samples is similar to the number of positive samples
- Negative sampling is proportion to the frequency of the words

11

11

# Sentiment Analysis

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- Determining whether a comment expresses positive or negative sentiment.
  - All of the car-based crap is just a huge product placement for Audi, and it really hurts credibility.
  - The movie is full of other great visuals like V.I.K.I., the whole robotized city of Chicago, and of course Smith's cool Audi.



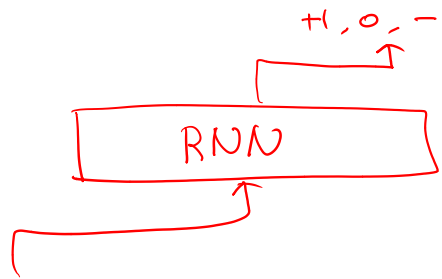
12

12

# RNN for sentiment analysis

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- A sentiment predictor trained on customer reviews of media content.
- There is an underlying function that tells whether any statement is positive, neutral, or negative



All of the car-based crap is just a huge product placement for Audi, and it really hurts credibility.

13

13

# Context-Free grammars

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- The notation for context-free grammars (CFG) is sometimes called Backus-Naur Form (BNF)
- A CFG consists of
  - A set of terminals  $T$
  - A set of non-terminals  $N$
  - A start symbol  $S$  (a non-terminal)
  - A set of productions  $X \rightarrow Y$

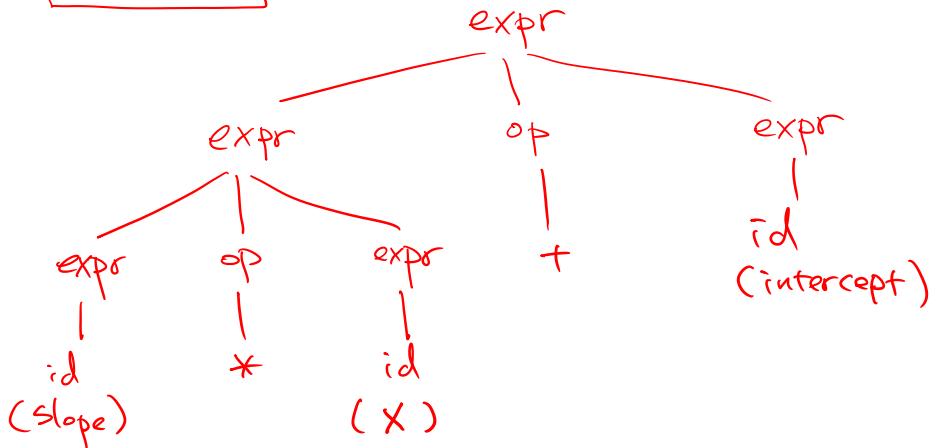
14

14

# Parse tree

$expr \rightarrow id \mid number \mid - expr \mid ( expr )$   
 $\mid expr \ op \ expr$   
 $op \rightarrow + \mid - \mid * \mid /$

- Parse tree for expression grammar for "slope \* x + intercept"

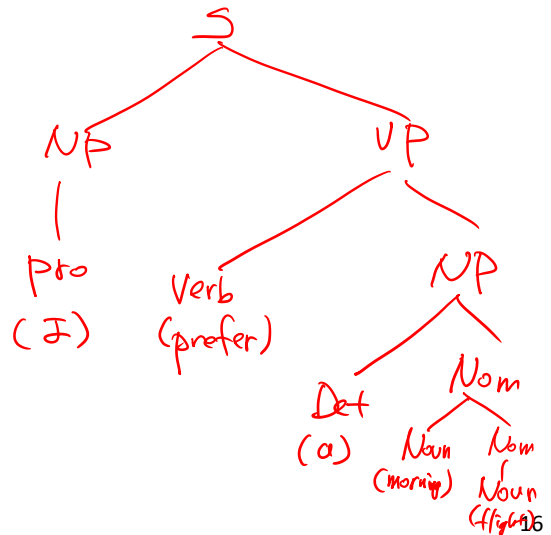


15

15

## CFG

- $S \rightarrow NP \ VP$
- $NP \rightarrow$  Pronoun  
| Proper-Noun  
| Det Nominal
- $Nominal \rightarrow$  Noun Nominal  
| Noun
- $VP \rightarrow$  Verb | Verb NP  
| Verb NP PP  
| Verb PP
- $PP \rightarrow$  Preposition NP
- I prefer a morning flight

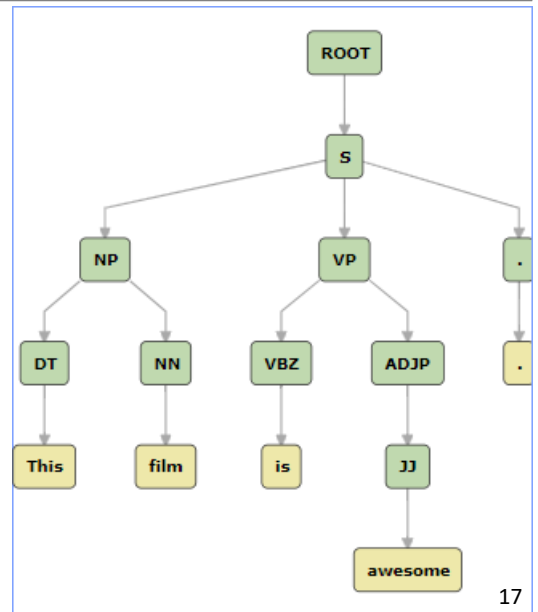


16



# Recursive Neural Network

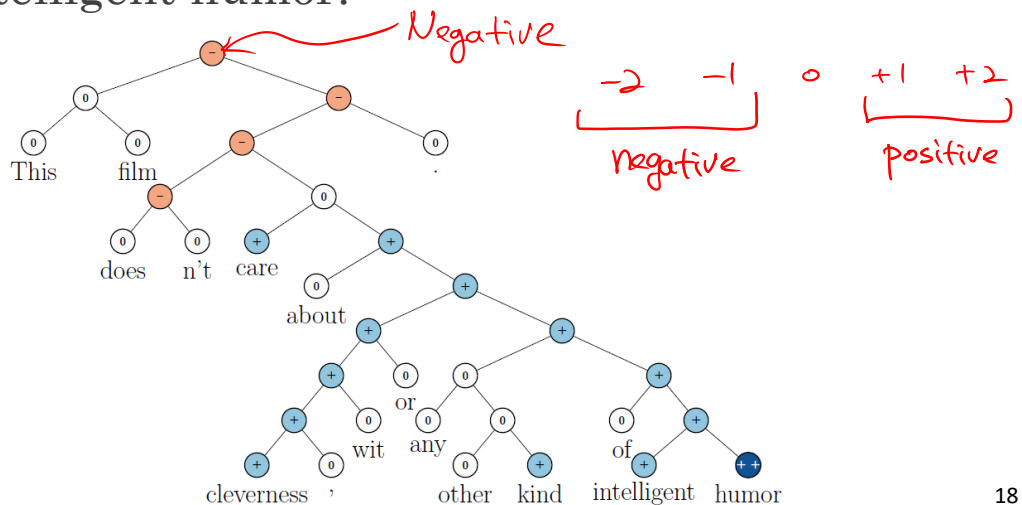
- Recursive neural networks represent another generalization of recurrent networks which is structured as a deep tree
- This film is awesome.



17

# Recursive Neural Network

- This file doesn't care about cleverness, wit or any other kind of intelligent humor.



18

# Recursive Neural Network

- To classify  $d$ -dimensional semantic vectors into five sentiment classes, the posterior probability is computed

$$\text{by } y_j = \frac{e^{(W_s \vec{x})_j}}{\sum_{i=1}^5 e^{(W_s \vec{x})_i}} \quad \begin{matrix} |W_s| = 1 \times d \\ |\vec{x}| = d \times 1 \end{matrix}$$

- The semantic vectors of internal nodes are computed by

$$\vec{x}_p = \tanh \left( \underbrace{\begin{bmatrix} \vec{x}_L \\ \vec{x}_R \end{bmatrix}^T}_{\text{matrix}} \underbrace{\vec{V}}_{\text{vector}} \underbrace{\begin{bmatrix} \vec{x}_L \\ \vec{x}_R \end{bmatrix}}_{\text{matrix}} + \underbrace{\vec{W}}_{\text{vector}} \underbrace{\begin{bmatrix} \vec{x}_L \\ \vec{x}_R \end{bmatrix}}_{\text{matrix}} \right)$$

