ELMO: Embeddings from Language Models

Ramaseshan Ramachandran

TABLE OF CONTENTS

1. Traditional Word Representations
   - Static Representation of word vectors
   - Latent Relationship
   - Contextual Word Representation
   - Contextual Word Representation
2. Sequence to Sequence Models
   - Seq2Seq
3. Layer Notmalization
4. Formula and Process
5. How it Works
6. Introduction
7. ELMo Architecture
8. Character-based Word Embeddings
9. Bidirectional Language Model
10. ELMO Embeddings
11. Training the ELMO Model
12. Benefits of ELMo
13. Conclusion
14. Various NLP Tasks
    - Question Answering
    - Textual Entailment
    - Sentiment Analysis
    - Semantic Role Labeling
    - Named Entity Extraction
    - Coreference Resolution
15. References

SENSE DISAMBIGUATION OF THE WORD BANK

Synset('bank.n.01')	sloping land (especially the slope beside a body of water)
Synset('depository-financial-institution.n.01')	a financial institution that accepts deposits and channels the money into lending activities
Synset('bank.n.03')	a long ridge or pile
Synset('bank.n.10')	a flight maneuver; aircraft tips laterally about its longitudinal axis (especially in turning)
Synset('bank.v.02')	enclose with a bank
Synset('bank.v.03')	do business with a bank or keep an account at a bank
Synset('bank.v.04')	act as the banker in a game or in gambling
Synset('bank.v.05')	be in the banking business
Synset('deposit.v.02')	put into a bank account
Synset('trust.v.01')	have confidence or faith in

SENSE DISAMBIGUATION - THE WORD PROGRAM

Synset(’plan.n.01’)	a series of steps to be carried out or goals to be accomplished
Synset(’program.n.02’)	a system of projects or services intended to meet a public need
Synset(’broadcast.n.02’)	a radio or television show
Synset(’platform.n.02’)	a document stating the aims and principles of a political party
Synset(’program.n.05’)	an announcement of the events that will occur as part of a theatrical or sporting event
Synset(’course_of_study.n.01’)	an integrated course of academic studies
Synset(’program.n.07’)	(computer science) a sequence of instructions that a computer can interpret and execute
Synset(’program.n.08’)	a performance (or series of performances) at a public presentation
Synset(’program.v.01’)	arrange a program of or for
Synset(’program.v.02’)	write a computer program

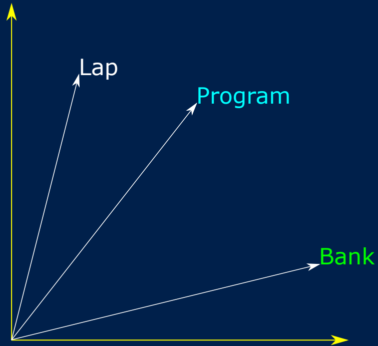
STATIC WORD REPRESENTATION

- Static representation of words
- Irrespective of the context, a polysemous word has the same vector representation
- Insensitive to the context in which they appear
- The word representation of a polysemous word is a biased representation due to certain context/pattern that appear more than any other context in the given corpus
- **It represents syntactic and semantic representations**
- **It does not represent the same word appearing in different linguistic contexts**

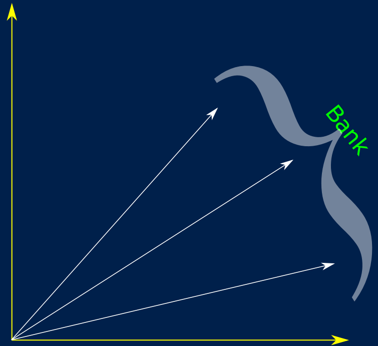
LATENT RELATIONSHIP

- The pairs of words that co-occur in similar patterns tend to have semantic relations. Using this property every word in the vocabulary is encoded as dense vectors using vector space semantic models.
- The individual dimension in the dense vectors is no longer intetpretable, except that its value may be proportional to the strength of the relationship it has with the rest of the words in the vocabulary
- The probabilistic language models use near-by contexts and do not represent any contextual representation of nearby sentences present in a corpus
- Is it possible to compute the contextual relationship amoung words, sentences and paragraphs?

CONTEXTUAL WORD REPRESENTATION



Static Word Representation



Contextual Word Representation of bank

CONTEXTUAL WORD REPRESENTATION

Boys are playing cricket near the Indian **bank**

A fundamental aircraft motion is a **banking** turn

Boys are playing cricket on Cauvery river **bank**

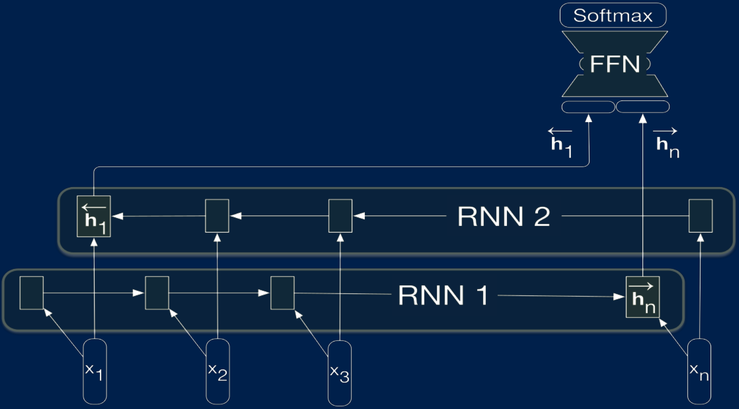
What is your **program** today?

Have you completed the **programming** assignment today?

A cultural **program** was telecast on TV

- The RNN layer holds the context specific representation of the words
- Why not use them for contextual word vector generation
- Can we use it for NLP tasks?
- Each token is assigned a representation $w_i = f(w_1, w_2, w_3, ...w_n)$ where n is the number of tokens/words in a sentence

BIDIRECTIONAL RNN WITH SINGLE OUTPUT[1]



A bidirectional RNN for sequence classification. The final hidden units from the forward and backward passes are combined to represent the entire sequence. This com-bined representation serves as input to the subsequent classifier.

TRAINING

- The next token in the sequence gets the largest probability mass
- If there are t words in the sequence $(w_1, w_2, w_3, \ldots, w_t)$, the transducer will have $t+1$ input and output neurons

$$\begin{aligned} p(w_{j+1}|w_1, w_2 \ldots, w_j) &= f(\mathrm{RNN}(\theta, w_1, w_2, \ldots, w_j)), \text{ where } j \in [1, t] \\ &= f(\mathrm{RNN}(\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_j)) \end{aligned}$$

  and $\hat{w}_j = p(w_j|\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_{j-1})$
- It is possible to create the next token using a conditional context, such as a topic or class of the current content, active or passive voice, etc.
- Example sentence generated without a context
  - *determine the time it takes a piece of glass to hit the ground?* ***A car drives straight off the edge of a cliff***
- Example sentence with context
  - *determine the time it takes the ball to hit the ground,* ***if it is dropped from a height of 45m***.

SEQ2SEQ-BASED APPLICATION

- **Next word/sentence prediction**

  Train pairs of consecutive sentences to generate a contenxt sensitive sentences in a sequence

- **Question-Anwering**

  Given a question (including word problems), find context sensitive answers

- **Auto-encoding**

  Building sentence vectors for identifying similar sentences - extending the distributional hypothsis of words into sentences

- **Machine Translation**

  Given pairs of language texts for training, trsnslate an unknown sentence usig the trained model

- **Precise writing**

  Given a long paragraph, compress into one two sentences

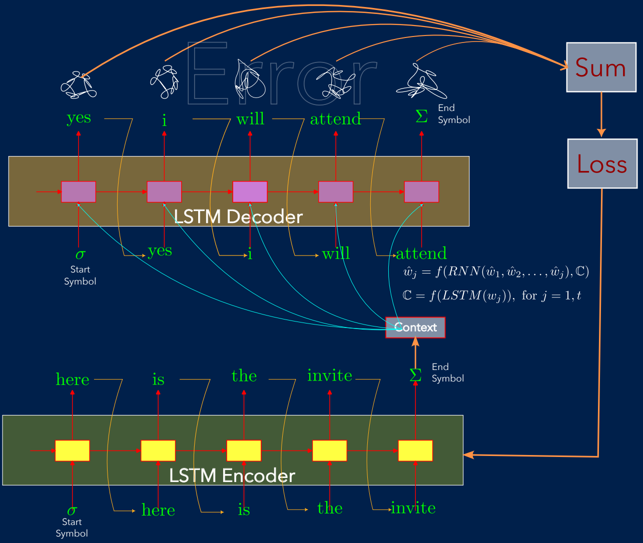
- **Title generation**

  Given abstract and title pairs, train and generate title for any new abstract

- **Chatbots**
- **Discourse Analysis**

  Analysis of written, spoken, sign language

SEQUENCE TO SEQUENCE GENERATOR



$$\hat{w}_j = f(RNN(\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_j), \mathbb{C})$$

$$\mathbb{C} = f(LSTM(w_j)), \text{ for } j = 1, t$$

WHAT IS LAYER NORMALIZATION?

- Layer Normalization (LayerNorm) is a technique used to normalize the inputs across the features for each training example.
- It helps in stabilizing the learning process in deep neural networks.

LAYER NORMALIZATION FORMULA

Given a vector $x = [x_1, x_2, \ldots, x_d]$, the layer norm is given by $\text{LayerNorm}(x) = \gamma \cdot \frac{x-\mu}{\sigma} + \beta$ where μ is the mean of x, σ is the standard deviation of x and γ and β are learnable scale and shift parameters

STEPS OF LAYER NORMALIZATION

1. Compute the mean μ of the input vector x. $\mu = \frac{1}{d}\sum_{i=1}^{d} x_i$
2. Compute the variance σ^2 of the input vector x. $\sigma^2 = \frac{1}{d}\sum_{i=1}^{d}(x_i - \mu)^2$
3. Normalize the input by subtracting the mean and dividing by the square root of variance. $\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \epsilon}}$ where ϵ is a small constant for numerical stability.
4. Scale and shift the normalized values. $y_i = \gamma \hat{x}_i + \beta 4$

INTRODUCTION TO ELMO

- ELMo (Embeddings from Language Models) is a deep contextualized word representation model.
- Proposed by Peters et al.[2], ELMo captures complex syntactic and semantic characteristics of words.
- ELMo embeddings are context-sensitive, varying for each instance of a word depending on its context.

ELMO ARCHITECTURE OVERVIEW

- ELMo uses a bidirectional LSTM language model with two layers to produce context-sensitive embeddings.
- The model is pre-trained on a large text corpus in an unsupervised manner.
- Key components:
  - **Character-based Embeddings**: Word embeddings are computed from character-level CNNs.
  - **Bidirectional LSTMs**: Separate LSTMs for forward and backward contexts.
  - **Layer-wise Aggregation**: Different layers are combined for task-specific representations.

CHARACTER-BASED EMBEDDINGS

- Character-based embeddings allow ELMo to handle out-of-vocabulary (OOV) words and morphological variations.
- The character RNN processes each word as a sequence of characters to produce a word embedding.
- This embedding captures both morphological and orthographic information.

$$\mathbf{w} = \mathsf{RNN}_{\mathsf{char}}(c_1, c_2, \ldots, c_n)$$

where $c_1, c_2, \ldots, c_n$ are the characters of the word.

BIDIRECTIONAL LANGUAGE MODEL (BILM)

- ELMo uses a bidirectional language model (BiLM) consisting of:
  - **Forward LSTM**: Processes words from left to right.
  - **Backward LSTM**: Processes words from right to left.
- Each LSTM layer l produces hidden states for each token t:

$$\overrightarrow{\mathbf{h}}_t^{(l)} = \mathrm{LSTM}_{\mathrm{forward}}(\mathbf{w}_{1:t})$$

$$\overleftarrow{\mathbf{h}}_t^{(l)} = \mathrm{LSTM}_{\mathrm{backward}}(\mathbf{w}_{t:T})$$

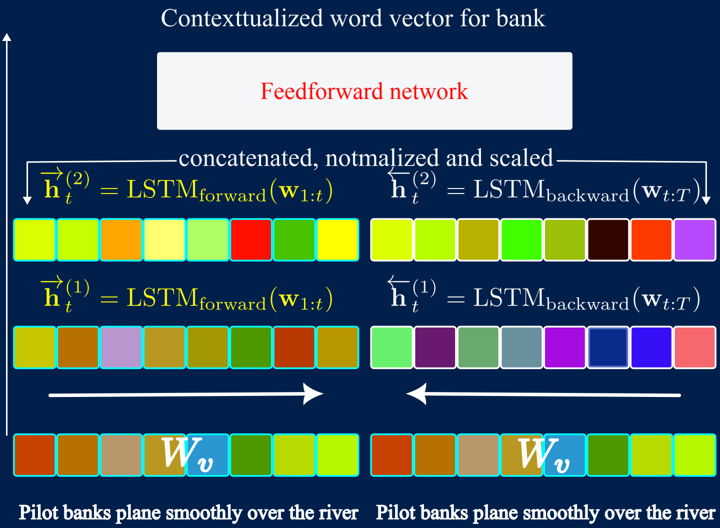
CONTEXTUALIZED ELMO EMBEDDINGS

ELMO embeddings are a weighted combination of hidden states from different layers:

$$\mathbf{ELMO}_t = \gamma \sum_{l=0}^{L} s^{(l)} \cdot \left[\overrightarrow{\mathbf{h}}_t^{(l)} ; \overleftarrow{\mathbf{h}}_t^{(l)} \right]$$

where $s^{(l)}$ are Layer-wise normalized weights using softmax, learned as task-specific parameters, γ is the scaling parameter to adjust the overall magnitude and $\left[\overrightarrow{\mathbf{h}}_t^{(l)} ; \overleftarrow{\mathbf{h}}_t^{(l)} \right]$ are the concatenated hidden states from forward and backward LSTMs.

ELMO ILLUSTRATION



Contexttualized word vector for bank

Feedforward network

concatenated, notmalized and scaled

$\overrightarrow{\mathbf{h}}_t^{(2)} = \text{LSTM}_{\text{forward}}(\mathbf{w}_{1:t})$

$\overleftarrow{\mathbf{h}}_t^{(2)} = \text{LSTM}_{\text{backward}}(\mathbf{w}_{t:T})$

$\overrightarrow{\mathbf{h}}_t^{(1)} = \text{LSTM}_{\text{forward}}(\mathbf{w}_{1:t})$

$\overleftarrow{\mathbf{h}}_t^{(1)} = \text{LSTM}_{\text{backward}}(\mathbf{w}_{t:T})$

W_v

W_v

Pilot banks plane smoothly over the river

Pilot banks plane smoothly over the river

TRAINING THE ELMO MODEL

- ELMO is pre-trained as a language model on a large text corpus
- The loss is computed as the sum of the forward and backward language model losses

  $$\mathbb{L}(\theta) = \sum_{t=1}^{T} (-\log p(w_t | w_{1:t-1}) - \log p(w_t | w_{t+1:T}))$$

  This includes the parameters of the feedforward weights
- After pre-training, the model is fine-tuned by learning task-specific weights $s^{(l)}$ for each layer.

BENEFITS OF ELMO

- ELMo is a task specific combination of the intermediate layer representations in the biLM[2]
- ELMo embeddings are context-sensitive, making them highly effective for tasks requiring nuanced word representations
- They capture complex syntactic and semantic relationships that static embeddings (e.g., Word2Vec, GloVe) cannot
- ELMo is designed to generalize across multiple NLP tasks, providing task-agnostic pre-trained embeddings

CONCLUSION

- ELMo represents a significant advancement in word embeddings by introducing context-dependent representations
- Its architecture, based on character-level embeddings and bidirectional LSTMs, provides a flexible and powerful approach for a range of NLP tasks
- ELMo set the stage for further innovations in contextual embeddings, leading to models like BERT and GPT

INTRODUCTION TO NLP TASKS

- Natural Language Processing (NLP) includes various challenging tasks that require advanced techniques and models
- This presentation covers six critical NLP tasks and explores models that perform well on each task

QUESTION ANSWERING

- **Task**: Answering questions based on provided context or general knowledge.
- **Example**:
  - **Context**: "The cat sat on the mat."
  - **Question**: "Where did the cat sit?"
  - **Answer**: "On the mat."
- **Models**: Bidirectional Encoder Represetation from Tansformers (BERT), Bidirectional Attention Flow (BiDAF), Transformer-based QA models

TEXTUAL ENTAILMENT

- **Task**: Determine if one piece of text (hypothesis) can be inferred from another (premise)
- **Example**:
  - **Premise**: ”All birds can fly.”
  - **Hypothesis**: ”Penguins can fly.”
  - **Entailment**: False (since penguins are birds but cannot fly)
- **Models**: Decomposable Attention Model, BERT, ESIM (Enhanced Sequential Inference Model)

SENTIMENT ANALYSIS

- **Task**: Classify text based on its sentiment (positive, negative, neutral).
- **Example**:
  - **Text**: "The movie was fantastic!"
  - **Sentiment**: Positive
- **Models**: LSTM, BERT, CNN for text, Attention-based models.

SEMANTIC ROLE LABELING

- **Task**: Identify and classify the arguments (participants) of a predicate in a sentence
- **Example**:
  - **Sentence**: "John broke the vase."
  - **Predicate**: "broke"
  - **Arguments**:
    - **Agent (who did it)**: John
    - **Patient (what was affected)**: the vase
  - **Models**: RNN-based models, BiLSTM, and Transformer models with SRL-specific adaptations

NAMED ENTITY EXTRACTION

- **Task**: Identify and classify named entities (e.g., person, organization, location) in text
- **Example**:
  - **Text**: ”Elon Musk founded SpaceX.”
  - **Entities**:
    - **Person**: Elon Musk
    - **Organization**: SpaceX
  - **Models**: BiLSTM-CRF, BERT for NER, and CNN-BiLSTM-CRF

COREFERENCE RESOLUTION

- **Task**: Identify all expressions that refer to the same entity in a text
- **Example**:
  - **Text**: ”Mary went to the store. She bought some milk.”
  - **Coreference**: ”Mary” and ”She” refer to the same person

SUMMARY OF TASKS

- These tasks represent key challenges in natural language understanding
- Each task requires different techniques and models, often combining rule-based, statistical, and deep learning approaches.
- Advanced neural models, especially Transformer-based architectures, have significantly improved performance on these tasks
- Continued development in neural architectures is expected to further enhance capabilities across NLP. More importantly, these tasks are used for evaluating the word embedding models, large Language models

REFERENCES I

[1] Daniel Jurafsky and James H. Martin. *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. Third Edition draft. 2024. URL: https://web.stanford.edu/~jurafsky/slp3/.

[2] Matthew E. Peters et al. “Deep contextualized word representations”. In: *CoRR* abs/1802.05365 (2018). arXiv: 1802.05365. URL: http://arxiv.org/abs/1802.05365.