Language Modeling

Machine Learning for Natural Language Processing, ENSAE 2022

Lecture 4

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Lectures Outline

1. The Basics of Natural Language Processing (February 1st)
2. Representing Text with Vectors (February 1st)
3. Deep Learning Methods for NLP (February 8th)
4. **Language Modeling (February 8/15th)**
5. Sequence Labelling (Sequence Classification) (February 15th)
6. Sequence Generation Tasks (February 15th)

Outline

- **Causal Language Model with LSTM**
- **Causal Language Model with Transformers**
- **Evaluation**

Framework

Given $(t_1, ..t_D) \in V^D$, our goal is to estimate: $P(t_{n+1}|t_1, .., t_n)$

We saw how to estimate that with n-gram models

To do better:

➔ Use a Deep-Learning Model

Why Deep Learning Models for LM?

Motivations

Theoretical Insights

- Deep Learning Models are **universal approximators**
- Recurrent Neural Network can in theory model infinite context

Practical Insights

- They can be trained on **very large amount of data**
- They can use **continuous representation** of input tokens capturing the *distributional hypothesis* efficiently

Framework

Given $(t_1, ..t_D) \in V^D$, **our goal is to estimate**:

$$\boxed{p(t_{n+1}|t_1, .., t_n)}$$

Framework

We want to find dnn_θ

$$\boxed{\begin{aligned} dnn_\theta : \quad & V^D \quad \rightarrow \quad [0,1]^V \\ & (t_1, .., t_D) \mapsto \hat{p} \end{aligned}}$$

$$\text{s.t. } \hat{p} = (p_i)_{i \in [|0, V-1|]}, \ \forall \ i \ \ p_i \in [0,1] \ \text{ and } \sum_i p_i = 1$$

Design Questions

- ★ **What tokenization ?**
- ★ **What output activation function and loss?**
- ★ **What architecture?**
- ★ **How do you represent a token to feed the model?**

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NB: Questions to ask for any NLP task approached with Deep Learning

Tokenization

- **Word-Level Tokenization: *e.g.*** ***"I, am, going"***

Pros: Easy to segment, Words are Linguistic Units
Cons: Out-of-Vocabulary (OOV) problem

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Pros: No OOV problem
Cons: Very long sequences

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Cons: Very long sequence

- **SentencePiece Tokenization:** *"_I, _am, _go, ing"*

Frequent "words" become tokens and infrequent ones are split into subwords

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Pros: No OOV problem
Cons: Very long sequence

- **SentencePiece Tokenization:** ***"_I, _am, _go, ing"***

Frequent "words" are kept intact and infrequent ones are split into subwords
NB: SentencePiece is the most popular tokenization algorithm for language models

Output Activation & Loss

Softmax Function

$$softmax(s) = \left(\frac{e^{s_i}}{\sum_k e^{s_k}}\right)_{i \in [|1, V|]}, \text{for } s \in \mathbb{R}^V$$

Loss Function

$$l(p, \hat{p}) = CE(p, \hat{p}) = \sum_{i \in [|0, V-1|]} p_i \, log(\hat{p}_i)$$

Output Activation & Loss

Softmax Function

$$softmax(s) = \left(\frac{e^{s_i}}{\sum_k e^{s_k}}\right)_{i \in [|1, K|]}, \text{ for } s \in \mathbb{R}^K$$

Loss Function

$$l(p, \hat{p}) = CE(p, \hat{p}) = \sum_{i \in [|0, V-1|]} p_i \, log(\hat{p_i})$$

NB: We will use them in all the tasks we will cover in this course

Architecture

- The Multi-Layer Perceptron
- Recurrent Neural Network: LSTM Model
- The Transformer

MLP for Language Modeling

Recall: The **MLP** works **on unidimensional data** (e.g. dimension *d*)

$$
\begin{aligned}
dnn_\theta : \quad \mathbb{R}^d &\rightarrow [0,1]^V \\
X &\mapsto \hat{Y}
\end{aligned}
$$

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How can we model $(t_1, ..t_D) \in V^D$ with *D* **arbitrary high ?**

➔ Truncate input sequences: **Fixed-Window Language Modeling**

How to represent input tokens?

Solution 1

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1. 1-Hot Encoding

How to represent input tokens?

Solution 1: 1-Hot Encoding

1. We associate each *token to a **1-hot vector of size D***

movie = [1, 0, ...,0, 0, 0]
hotel = [0, 1, ..., 0, 0, 0]
...
art = [0, 0,..., 0, 0, 1]

2. **Concatenate them** to get a unidimensional vector

1-Hot Encoding as inputs

$$dnn_\theta : \quad \{0,1\}^{|V|*K} \rightarrow [0,1]^V$$
$$x = ([x_1, .., x_K]) \mapsto \hat{p}$$

- ➔ First hidden layer is of size ***|V|*K***
- ➔ Taking as input **a sparse vector**

1-Hot Encoding as inputs

$$dnn_\theta : \quad \{0,1\}^{|V|*K} \rightarrow [0,1]^V$$
$$x = ([x_1, .., x_K]) \mapsto \hat{p}$$

First hidden layer:
assuming tanh as the activation function, dimension δ

$$h_1 = tanh(W.x) \text{ s.t. } W \in \mathbb{R}^{\delta \times (|V| * K))}$$

1-Hot Encoding as inputs

$$dnn_\theta : \quad \{0,1\}^{|V|*K} \rightarrow [0,1]^V$$

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Limits

➔ The representation of each token is fixed and a 1-hot vector

➔ In this approach, **we do not learn** a representation of **each input token**

How to represent input tokens?

Solution 2: Integrate an Dense Embedding Layer

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We define a dense embedding layer $E \in \mathbb{R}^{\delta_e \times |V|}$.

This means that for each token $t \in V$ indexed by j in the vocabulary $V = \{t_1, .., t_{|V|}\}$) we have t_j *embedded* by the vector $E_{.j}$ (i.e. column of the matrix E indexed by j) of dimension δ_e (the dimension of the embedding vectors).

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➔ ***E* is part of the parametrization** of the model like any other layers

➔ We can train it during **backprop end-to-end**

See how to define it in torch

Dense Embedding Layer

$$dnn_\theta : \boxed{\mathbb{R}^{|K|*\delta_e}} \rightarrow [0,1]^V$$

$$x = ([x_1, .., x_K]) \mapsto \hat{p}$$

s.t. $x_i = E_{.j} \in \mathbb{R}^{\delta_e}$ with token t_i indexed by j in V

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- ➔ *E* is a dense embedding matrix
- ➔ We can **learn** a **representation vector** for **each token in the vocabulary**

Why is an Embedding Layer much better?

Trainable Dense Embedding layers are a **“game changer“** for Deep Learning Models in NLP i.e. Generalization is much better compared to 1-hot encoding

Why? **(intuition)**

t and t' that have the embedding vectors (in E) x and x'. e.g. $\boxed{t = \text{"dog"} \text{ and } t' = \text{"cat"}}$

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How to initialize an Embedding Layer?

Similarly to all other parameters in a deep learning model

- Before starting training: **we can simply initialize the embedding matrix randomly**
- Before training, the similarity between **embedding word vectors is random**

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Can we do better?

How to initialize an Embedding Layer?

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Can we do better?

➔ In lecture 2 we have seen how to represent good dense embedding vector with skip-gram word2vec model

➔ **We can simply initialize our word embedding matrix with word2vec vectors**

How to initialize an Embedding Layer?

Initializing with a **pretrained embedding** layer was also a ***gamechanger*** for many NLP tasks and many Deep Learning architecture

Conditions to use a pretrained embedding layer:

➔ The token in our vocabulary must be in the training of the word2vec model
➔ For the one that were not seen, we can simply initialize them randomly

Transfer Learning in NLP

Initializing with a **pretrained embedding** layer is also a ***game changer*** for many NLP tasks and many Deep Learning architecture

It is called Transfer Learning

Embedding Layer Summary

- Trainable Dense Embedding Layer are a *game changer* for Deep Learning Models
- Even more when we can use a pretrained embedding layers (e.g. with word2vec)
- They can be used with all Deep Learning Architectures
- **For all NLP tasks**

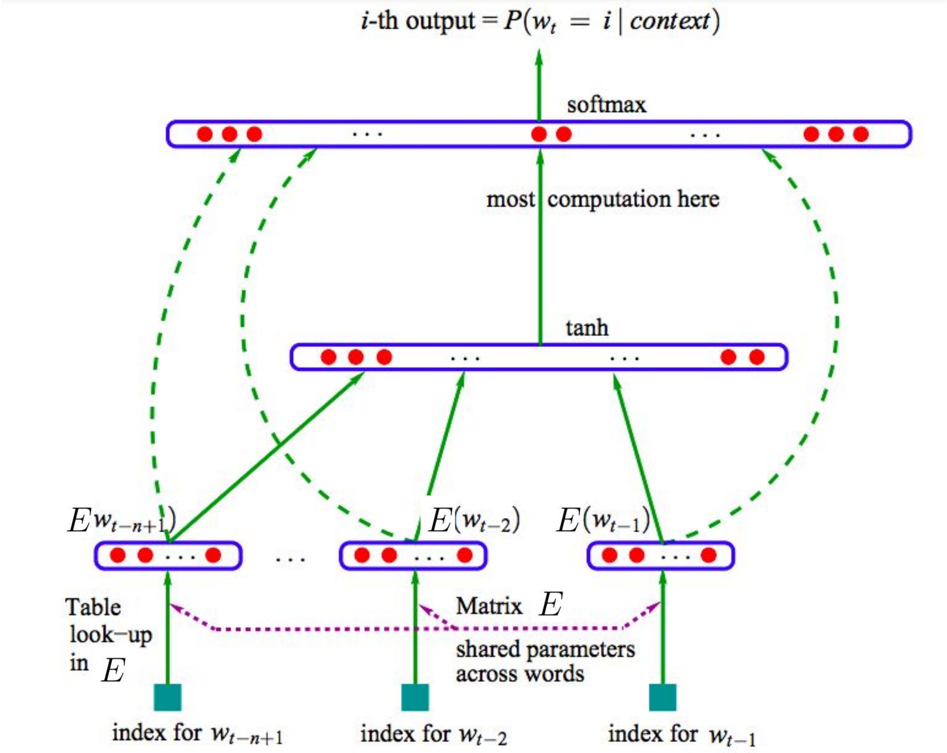
MLP for Fixed-Window Language Modeling

$$\boxed{\hat{t}_{n+1} = argmax_{t \in V}\, p(t|t_1, .., t_n)}$$

$$dnn_\theta : \quad \mathbb{R}^{|V| * \delta_e} \rightarrow [0, 1]^V$$

$$x = ([x_1, .., x_K]) \mapsto \hat{p}$$

MLP for Fixed-Window Language Modeling



Limits of MLP for language modeling

- ***Windows*** **is Fixed**

➔ **Use Recurrent Neural Network (e.g. LSTM)**

Recurrent Neural Network for LM

Recall:

$$h_{i+1,t+1} = \varphi_i(W_i h_{i,t} + U_i h_{i+1,t} + +b_i), \forall\, i \in [|1, L-1|]$$

$$\text{with } h_{1,t} = X_t \text{ and } \hat{Y}_t = dnn(X_t) = h_{L,t} \,\forall\, t \in [|1, T-1|]$$

Recurrent Neural Network for LM

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For Language Modeling , like we did for the MLP

- ~~We use an Embedding layer~~
- We use the softmax layer as output

Recurrent Neural Network for LM

For an sequence of token

$$h_{i+1,t+1} = \varphi_i(W_i h_{i,t} + U_i h_{i+1,t} + b_i), \forall\, i \in [|1, L|]\ \forall\, t \in [|1, T|]$$

$$\text{with } h_{1,t} = Emb(x_t) \text{ and } \hat{p_{t+1}} = h_{L+1,t+1}$$

$$\text{with } \varphi_L = softmax$$

We estimate $\boxed{\hat{p_{t+1}} = p(x_{t+1}|x_1, ..x_t)}$ **directly with the RNN**

Recurrent Neural Network for LM

Written in a more synthetic way

$$h_{i+1,t+1} = RNN_i(h_{i,t}, h_{i+1,t}), \forall\, i \in [|1, L|]\; \forall\, t \in [|1, T|]$$

$$\text{with } \; h_{1,t} = Emb(x_t) \; \text{ and } \; \hat{p_{t+1}} = h_{L+1,t+1}$$

$$\text{with } \; \varphi_L = softmax$$

We estimate $\boxed{\hat{p_{t+1}} = p(x_{t+1}|x_1, ..x_t)}$ **directly with the RNN**

Recurrent Neural Network for LM

With a LSTM, we have a dependency on the *Cell* Vector:

$$h_{i+1,t+1}, C_{i+1,t+1} = LSTM_i(h_{i,t}, h_{i+1,t}, C_{i+1,t}), \forall\, i \in [|1, L|]\, \forall\, t \in [|1, T|]$$

$$\text{with } h_{1,t} = Emb(x_t) \text{ and } \hat{p_{t+1}} = h_{L+1,t+1}$$

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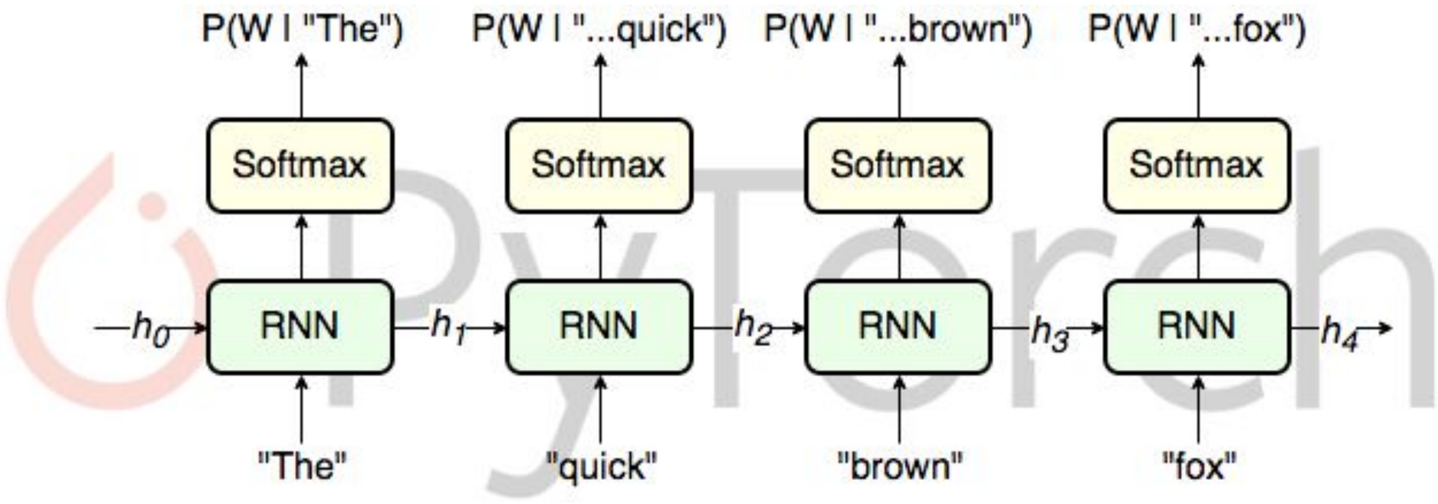
Recurrent Neural Network for LM



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Transformer for Causal Language Modeling

Inputs: Transformers requires a fixed sequence at input (we note it $\mathcal{T}$)

Let's assume we have a sequence $(x_1, ...x_T)$

We simply append it with a ***PADDING*** token

$$\text{We append } (x_{T+1}, .., x_{\mathcal{T}}) \text{ with } \quad x_t = [PAD] \, \forall \, t \geq T+1$$

We get a sequence of length $\mathcal{T}$ **:** $(x_1, ...x_{\mathcal{T}})$

We make the model ignore those tokens by setting the softmax scores to 0 in the self-attention

Transformer for Causal Language Modeling

Input **Embeddings:**

$$(x_1, ...x_T)$$

Embedding: $$(Emb(x_1), ...Emb(x_T))$$

such that $$Emb(x_i) = PositionEmb(x_i) + TokenEmb(x_i)$$

Transformer for Causal Language Modeling

Given a sequence of tokens: $(x_1, .., x_T)$

$$\mathrm{H}_{i+1} = FeedForward(A_{i+1}) \text{ and } A_{i+1} = SelfAttention(H_i) \quad \forall\, i \in [|1, L|]$$

$$\text{with} \quad SelfAttention(\mathrm{H}_i) = softmax(\frac{Q\,K^T}{\sqrt{\delta_K}})V$$

$$\mathrm{H}_0 = (Emb(x_1), ...Emb(x_T))$$

Transformer for Causal Language Modeling

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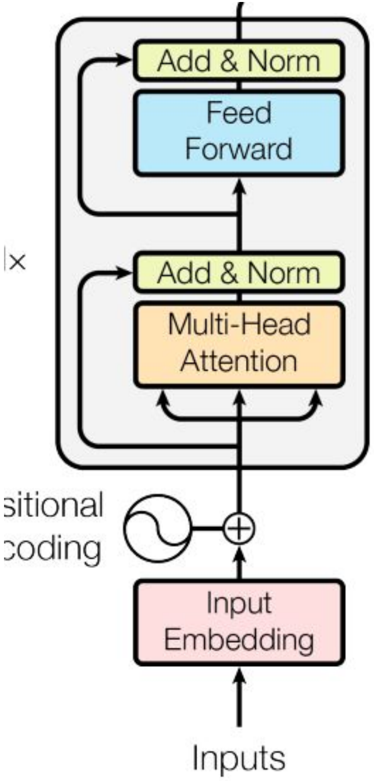
$$\mathrm{H}_0 = (Emb(x_1), ...Emb(x_T))$$

- **Residual Connection** and **Layer Norm** are not included in those equations
- **FeedForward is position-wise** two layer MLP (i.e. applied independently from the position of each hidden vector)
- Self-Attention is actually a **Multi-Head Self-Attention**

The Transformer Architecture

The Transformer Architecture is

- Stack of [Self-Attention + FF Layer]
- With Skip-Layer and Normalization Layers in between
- Encoding the position with positional vector



Transformer for Causal Language Modeling

Given a sequence of tokens: $(x_1, .., x_T)$

⇒ **Last element of the sequence of the hidden states** of the last layer fed to a softmax

$$\boxed{p_{\hat{x_{T+1}}} = softmax(h_T) \ \ \forall t \leq \ T}$$

Training

- We train on large corpus of text (+1G of text)
- We train them with backpropagation
- We usually do "teacher-forcing", for each step, we use the "gold" sequence" and not the predicted one
- For Transformers, we train on sequences as long as possible (~1000 tokens)

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Evaluation

$$perplexity(\hat{x}, x) = 2^{-\sum_i x_i log(\hat{x}_i)}$$

The lower the perplexity the better the language model

source

Empirical Performance

Language Model Performance Comparison

➔ **Transformer Models outperform LSTM-based models**

Lecture Summary

- Causal Language Modeling Framework
- Representing input tokens for language modeling
- Recurrent Neural Network for Language Modeling
- Transformer for Language Modeling