An Overview of Natural Language Processing

Sina Semnani
CS294S May 5, 2020

some slides are adopted from Giovanni Campagna
Outline

- Introduction
- Deep Learning for Natural Language Processing
- Word Representation
  - One-hot
  - Dense
  - Language Models
  - Contextual
- Sequence to Sequence
- Attention
Natural Language Processing

• How do we map from text to integers/real numbers/text
• Examples:
  • Text Classification
  • Question Answering
  • Semantic Parsing
Natural Language Processing

• How do we map from text to integers/real numbers/text
• Examples:
  • Text Classification
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  • Semantic Parsing

the writer-director has made a film so unabashedly hopeful that it actually makes the heart soar.

Input

Output +1 (positive)
Natural Language Processing

• How do we map from text to integers/real numbers/text
• Examples:
  • Text Classification
  • Question Answering
  • Semantic Parsing

Paragraph: ... With a population of 3,792,621, Los Angeles is the most populous city in California and ...

Question: What is the population of Los Angeles?

Answer: 3,792,621
Natural Language Processing

• How do we map from text to integers/real numbers/text
• Examples:
  • Text Classification
  • Question Answering
  • Semantic Parsing

Input

Show me Chinese restaurants in Palo Alto.

Output

```
now => @QA.restaurant(), geo == makeLocation("Palo Alto") && servesCuisine ~= "Chinese" => notify
```
NLP Has Been Especially Successful in Recent Years

- Even “super-human”, according to some benchmarks for Question Answering, Natural Language Inference, etc.

"Human" performance is 90.5%
But Not Entirely ...
 But Not Entirely ...

- Reported human performance can be misleading
- These models are very fragile and lack common sense
- Some adversarial tests result in a 2-10x accuracy drop while humans are unaffected
But Not Entirely …

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**Paragraph:** Its counties of Los Angeles, Orange, San Diego, San Bernardino, and Riverside are the five most populous in the state and all are in the top 15 most populous counties in the United States.

**Question:** What is the smallest geographical region discussed?

**Answer:** Riverside
But Not Entirely ...

• Reported human performance can be misleading
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**Paragraph:** Its counties of Los Angeles, Orange, San Diego, San Bernardino, and Riverside are the five most populous in the state and all are in the top 15 most populous counties in the United States. *a simplest geographic regions discuss donald trump.*

**Question:** What is the smallest geographical region discussed?

**Answer:** donald trump
But Not Entirely ...

- Besides, we have not even come close to humans on many other tasks
  - Understanding nontrivial dialogues
  - Multilingual tasks and low-resource languages
  - Empathetic text generation
  - Advice giving
  - Common sense
  - ...

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Neural Networks for Natural Language Processing
Before Deep Learning for Natural Language

• NLP research was focused on rule-based approaches for a very long time
• 1960s: ELIZA
  • one of the first conversational systems
  • matched keywords and repeated the user
Before Deep Learning for Natural Language

- My existential discussion with ELIZA last night:
Before Deep Learning for Natural Language

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![Talk to Eliza](image)
Before Deep Learning for Natural Language

• My existential discussion with ELIZA last night:

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> Hello, I am Eliza.
* Hi, I'm a student at Stanford.
> Do you believe it is normal to be a student at Stanford?
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Before Deep Learning for Natural Language

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> Are you saying no just to be negative?
* Maybe?
> You aren't sure?
```
Deep Learning for Natural Language

- NLP research was focused on rule-based approaches for a very long time
- 1960s: ELIZA
  - one of the first conversational systems
  - matched keywords and repeated the user
- Rapid increase in the amount of available digital text and computational power has made deep learning a very suitable tool for natural language processing
- Today, almost all systems that process human language have a machine learning component and learn from large amounts of data
Machine Learning

- Arthur Samuel (1959): Machine Learning is the field of study that gives the computer the ability to learn without being explicitly programmed.

- Instead, we show the computer a lot of examples of the desired output for different inputs.
Machine Learning

• The goal is to learning a parametrized function
• The parametrized function can have various shapes:
  • Logistic Regression
  • Support Vector Machines
  • Decision Trees
  • Neural Networks

• Inputs and outputs can be many different things:
  • Text
  • Image
  • Integer
  • $y \in \mathbb{R}^m$
  • ...
  • Text
  • Image
  • Integer
  • $y \in \mathbb{R}^n$
  • ...

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Deep Learning

• The parametrized function is a combination of smaller functions
• Example: Feedforward Neural Network
  • An input vector $x$ goes to output vector $y$ using a combination of functions of the form $\text{output} = g(W \times \text{input} + b)$
  • $g(.)$ makes things nonlinear
Deep Learning

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\[ g(W_1x + b_1) \]

\[ x \]

input
Deep Learning

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\[
g(W_1 x + b_1) \rightarrow g(W_2 h_1 + b_2)
\]
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Deep Learning

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\]
Deep Learning

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$$
\begin{align*}
    &x &\rightarrow &g(W_1x + b_1) \rightarrow &g(W_2h_1 + b_2) \rightarrow g(W_3h_2 + b_3) \rightarrow &y \\
    &\text{input} &\rightarrow &h_1 &\rightarrow &h_2 &\rightarrow &\hat{y} &\rightarrow &y \\
    &\text{model prediction} &\rightarrow &\text{gold label}
\end{align*}
$$
Deep Learning

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    x & \rightarrow h_1 & \rightarrow h_2 & \rightarrow \hat{y} & \rightarrow y
\end{align*}
$$

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Loss Function and Gradient Descent

- Calculate gradient of loss with respect to parameters
- Iteratively update parameters to minimize loss
Loss Function and Gradient Descent

- Calculate gradient of loss with respect to parameters
- Iteratively update parameters to minimize loss

\[ \theta^{\text{new}} = \theta^{\text{old}} - \alpha \nabla \theta J(\theta) \]
Word Representation: One-Hot Vectors

- We have a calculus for functions that are from $\mathbb{R}^n$ to $\mathbb{R}^m$
- So we have to convert everything to vectors
- Consider the simple task of domain detection: 0 means is restaurants skill, 1 means everything else
Word Representation: One-Hot Vectors

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0/1

Show me restaurants around here
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$$\text{restaurant} = [1 \ 0 \ 0 \ \ldots \ \ 0]$$
$$\text{diner} \quad = [0 \ 1 \ 0 \ \ldots \ \ 0]$$

... 

Show me restaurants around here
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...

Show me restaurants around here
Sequence Representation: Recurrent Neural Networks

- \( h_t, o_t = RNN(x_t, h_{t-1}; \theta) \)
- \( \theta \) is the learned parameters

- Various types of cells:
  - Gated Recurrent Unit (GRU)
  - Long Short-Term Memory (LSTM)
Encode Sequences

- Recurrent: repeat the same box, with the same $\theta$ for each word in the sequence

Show me restaurants around here
Encode Sequences

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Encode Sequences

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```
Show         me         restaurants         around         here
```

```
0/1
```

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Encode Sequences

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Encode Sequences

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```
Show           me             restaurants      around      here
RNN            RNN            RNN              RNN          RNN
```

0/1
Encode Sequences

- Recurrent: repeat the same box, with the same $\theta$ for each word in the sequence

Show me restaurants around here

Define $J(\theta)$
Encode Sequences

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```
Define $J(\theta)$
```

```
Show me restaurants around here
```

“Encodes” the input sentence into a fixed-size vector
Encode Sequences

- It can be Bi-directional
Encode Sequences

- It can be Bi-directional

Show me restaurants around here
Encode Sequences

• It can be Bi-directional
Encode Sequences

- It can be Bi-directional

Show me restaurants around here
Encoder

Converts a sequence of inputs to one or more fixed size vectors
Encoder

Converts a sequence of inputs to one or more fixed size vectors

Show me restaurants around here
Decoder

receives a fixed size vector and produces probability distributions over words, i.e. vectors of size $|V|$ whose elements sum to 1
In both assignments, the goal was to build a system that can convert natural sentences to their corresponding ThingTalk programs.

In HW2, you trained a semantic parser for this task. Do you think you used one-hot encoding for word representations? Why or Why not?
In both assignments, the goal was to build a system that can convert natural sentences to their corresponding ThingTalk programs. In HW2, you trained a semantic parser for this task. Do you think you used one-hot encoding for word representations? Why or Why not?

No. Just to name a few limitations of one-hot encoding: Large size of input would result in inefficient computations. Words with similar meanings would have nothing in common.
The Effect of Better Embeddings

- During training, neural networks learn to map regions of the input space to specific outputs.
- If word embeddings map similar words to similar regions, the neural network will have an easier job.

$$\text{restaurant} = [1 \ 0 \ 0 \ \ldots \ 0]$$
$$\text{diner} \quad = [0 \ 1 \ 0 \ \ldots \ 0]$$
$$\ldots$$
The Effect of Better Embeddings

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These sentences are in the restaurants domain
The Effect of Better Embeddings

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restaurant = [1 0 0 … 0]
diner = [0 1 0 … 0]
...

These sentences are in the restaurants domain

These are in the hotels domain
Word Representation: Dense Vectors

• Also called Distributed Representation
• In practice, ~100-1000 dimensional vectors (much smaller than $|V|$)
• Learned from large text corpora
Word Representation: Dense Vectors

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I went to this amazing restaurant last night.
We were at the diner when we saw him.
   Ali went to the movies.
   She was at the movies.
   ...

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Word Representation: Dense Vectors

- Also called Distributed Representation
- In practice, ~100-1000 dimensional vectors (much smaller than $|V|$)
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\[
J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{j=-m}^{+m} \log P(w_{t+j} \mid w_t ; \theta)
\]

I went to this amazing restaurant last night.
We were at the diner when we saw him.
   Ali went to the movies.
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   ...

Learn embeddings that maximize our ability to predict the surrounding words of a word.
Word Representation: Dense Vectors

Images from GloVe: Global Vectors for Word Representation (2014)
There exists a 300-dimensional vector $z$ such that if you add it to the vector of a city name, you get the vector of their zip codes!
Word Representation: Dense Vectors

• We have one vector $v$ for each word $w$.
• $d$ has to encode all aspects and meanings of $w$

• These two sentences will be almost identical in terms of word embeddings.

How much does a share of Apple cost?

How much does a pound of apple cost?

• We can do better
Language Modeling

• The task of estimating the probability of a sequence of words

\[ P(w_1w_2w_3 \ldots w_m) \]

• Usually requires simplifying assumptions

\[
P(w_1 \ w_2 \ w_3 \ldots \ w_m) = \prod_{i=1}^{m} P(w_i|w_1 \ldots w_{i-1})
\]

\[ \approx \prod_{i=1}^{m} P(w_i|w_{i-n} \ldots w_{i-1}) \]
Autoregressive Language Models

• Autoregressive: predict the next word
Autoregressive Language Models

- Autoregressive: predict the next word

Show me restaurants around here
Autoregressive Language Models

- Autoregressive: predict the next word

\[ P(\ . \ | \ \text{show}) \]

Diagram: Encoder with inputs "Show", "me", "restaurants", "around", "here".
Autoregressive Language Models

- Autoregressive: predict the next word

\[ P(\cdot | \text{show}) \quad P(\cdot | \text{show me}) \]

Encoder

- Show
- me
- restaurants
- around
- here
Autoregressive Language Models

- Autoregressive: predict the next word

\[ P(. | \text{show}) \quad P(. | \text{show me}) \quad \ldots \]

Diagram showing the encoder process with words such as "Show", "me", "restaurants", "around", and "here".
Masked Language Models

• Masked: fill in the blank
Masked Language Models

- Masked: fill in the blank

Show me _ around here
**Masked Language Models**

- Masked: fill in the blank

\[
P(\cdot | \text{show me } \_ \text{ around here})
\]
Word Representation: Contextual
Word Representation: Contextual

- Training data for a task is limited
- Pre-train a language model on a very large text corpus

- Embeddings from Language Models: ELMo (Oct. 2017)
- Generative Pre-training: GPT (June 2018)
- Bidirectional Encoder Representations from Transformers: BERT (Oct. 2018)
- GPT-2 (Feb. 2019)
- ...
Word Representation: Contextual

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<table>
<thead>
<tr>
<th>corpus size</th>
<th>800 million words</th>
</tr>
</thead>
<tbody>
<tr>
<td>1x</td>
<td>4x</td>
</tr>
<tr>
<td>48x</td>
<td></td>
</tr>
</tbody>
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A language model is trained to be good at predicting missing words. How can we test if the contextual representations learned by the language model are good at capturing the meaning of sentences as well?
A language model is trained to be good at predicting missing words. How can we test if the contextual representations learned by the language model are good at capturing the meaning of sentences as well?

1. By evaluating them on downstream tasks. BERT for instance improved state of the art results for several NLP tasks by 4-8%.
2. By looking at the representations themselves.
Sequence to Sequence
When Both Input and Output Are Sequences of Words
When Both Input and Output Are Sequences of Words

- Seq2Seq has many use cases
  - Machine Translation
  - Question Generation
  - Semantic Parsing

- We will use examples from semantic parsing
When Both Input and Output Are Sequences of Words

- **Seq2Seq** has many use cases
  - Machine Translation
  - Question Generation
  - Semantic Parsing

- We will use examples from semantic parsing

Show me restaurants around here now => @QA.Restaurant()
, geo == current_location => notify
Sequence to Sequence

- Dataset: pairs of source sentence \( x_1 x_2 \ldots x_s \) and target sentence \( y_1 y_2 \ldots y_t \)
- For instance, pairs of natural sentences and their ThingTalk programs
- The objective is to learn \( \theta \) that maximizes:

\[
J(\theta) = P(y_1 y_2 \ldots y_t \mid x_1 x_2 \ldots x_s ; \theta) = P(y_1 \mid x_1 x_2 \ldots x_s ; \theta) \times P(y_2 \mid y_1 x_1 x_2 \ldots x_s ; \theta) \times \ldots
\]
Encoder-Decoder

We can use encoder-decoder models for Seq2Seq tasks

Show me restaurants around here
Encoder-Decoder

We can use encoder-decoder models for Seq2Seq tasks

Show me restaurants around here

now => QA.Restaurant(), geo == ...

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Encoder-Decoder

In practice, we also input the previous token to the decoder
Encoder-Decoder

At training time, decoder always gets the **gold target** as input
Encoder-Decoder

At training time, decoder always gets the **gold target** as input.

Show me restaurants around here.
Encoder-Decoder

At training time, decoder always gets the gold target as input

Show me restaurants around here

<start> now => @QA.Restaurant()
Encoder-Decoder

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At training time, decoder always gets the **gold target** as input

These vectors define a distribution over all possible words. We define $J(\theta)$ based on the probability of the correct word.
Encoder-Decoder

- At generation time, we feed in the word generated by the decoder at previous time step.
- Pro: very fast to converge in practice
- Con: model is never exposed to its own search errors during training
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From Word Probabilities to Output Sequence

- Greedy decoding: at each step, pick the most probable word
  - Greedy decoding can make search errors: if we choose a wrong word at a step, we might never recover
- Beam Search: at each step, keep the K most probable observed outputs
- Sampling: pick a word at random according to the distribution
- ...
Downside of Word-Level Loss

Source: Show me restaurants around here.

Gold target: now => @QA.Restaurant() , geo == current_location => notify

Model output: now => @QA.Hospital() , geo == current_location => notify

Most of the sentence is the same as the gold, so low cost, but you will –literally- end up in a hospital!

A small difference in words is not the same as a small difference in meaning.
Downside of Word-Level Loss

**Source:** Show me nearby restaurants.

**Gold target:** mostrami ristoranti nelle vicinanze

**Model output:** sto cercando un ristorante qui attorno
(I’m looking for a restaurant around here)

Most of the sentence is different from the gold, so high cost, but the answer is correct.

Difference in words is not the same as difference in meaning.
Quiz

Is this a problem in semantic parsing as well?
Is this a problem in semantic parsing as well?

Not for ThingTalk. ThingTalk is normalized, that is, each meaning has exactly one ThingTalk code.
Attention
Capturing Long Term Dependencies is Important in NL

- When generating a word, the model has to look at multiple words that are potentially far from each other.

Alice is young, lively and beautiful  Alice è giovane, vivace e
bello
bella
Capturing Long Term Dependencies is Important in NL

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- Some words are more important than others
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How far away is the closest Italian restaurant to me?  now => [ distance ] of ( compute distance …
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• Some words are more important than others

  How far away is the closest Italian restaurant to me?

  now => [ distance ] of (compute distance...
Capturing Long Term Dependencies is Important in NL

- When generating a word, the model has to look at multiple words that are potentially far from each other.

Alice is young, lively and beautiful  \rightarrow  Alice è giovane, vivace e bella

- Some words are more important than others

How far away is the closest Italian restaurant to me?

now \Rightarrow [\text{distance}] \text{ of (compute distance ...}
Attention

• Designed to alleviate this exact problem
• At each decoding step, compute *attention scores* by combining encoder and decoder states
• Normalize scores with *softmax*
• Mix them into a *context vector*
• Mix decoder state and context vector
Encoder-Decoder with Attention

When generating a word for the output, directly look at all the words in the input

Show me restaurants around here  <start>
Encoder-Decoder with Attention

When generating a word for the output, directly look at all the words in the input
Transformer

• Is a relatively new class of parametrized functions
• Instead of RNNs, is entirely made up of attentions
• Attentions are easy to compute in parallel, which is especially beneficial when using GPUs
• Empirically, Transformer outperforms RNN in a wide range of tasks and datasets.
• Has encoder, decoder and Seq2Seq variants.
Remember This Image from Lecture 1?

Search : @Yelp.Restaurant, price == cheap & &  ...  

Decoder: LSTM + Attention + pointer (autoregressive)  

BiLSTM  

CoAttention  

Transformer  

Search : @Yelp.Restaurant,  ...  

CONTEXT  

BERT (pretrained)  

Do you have something cheap?  

QUESTION
Remember This Image from Lecture 1?

Search : @Yelp.Restaurant, price == cheap && ...  

Decoder: LSTM + Attention + pointer (autoregressive)  

BiLSTM  

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Search : @Yelp.Restaurant, ...

Do you have something cheap?

CONTEXT

QUESTION

contextual word embeddings
Remember This Image from Lecture 1?

Search : @Yelp.Restaurant, price == cheap && ...
Remember This Image from Lecture 1?

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Decoder: LSTM + Attention + pointer (autoregressive)

BiLSTM

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Search: @Yelp.Restaurant, ...

CONTEXT

BERT (pretrained)

Do you have something cheap?

QUESTION

contextual word embeddings
Remember This Image from Lecture 1?

Search : @Yelp.Restaurant, price == cheap && ...

Transformer

CONTEX

CoAttention

BiLSTM

Decoder: LSTM + Attention + pointer (autoregressive)

Do you have something cheap?

BERT (pretrained)

contextual word embeddings

a sequence of vectors
Remember This Image from Lecture 1?

- Search: @Yelp.Restaurant, price == cheap & & ... 
- Decoder: LSTM + Attention + pointer (autoregressive)
- BiLSTM
- CoAttention
- Transformer
- BERT (pretrained)

(a sequence of vectors) 

Search: @Yelp.Restaurant, ... 

CONTEXT

Do you have something cheap? 

QUESTION

contextual word embeddings
Remember This Image from Lecture 1?

Decoder: LSTM + Attention + pointer (autoregressive)

BiLSTM

CoAttention

Transformer

Search: @Yelp.Restaurant, price == cheap && ...

Do you have something cheap?

contextual word embeddings
Remember This Image from Lecture 1?

Decoder: LSTM + Attention + pointer (autoregressive)

Search: \texttt{@Yelp.Restaurant, price == cheap \&\& ...}

BiLSTM

CoAttention

Transformer

Search: \texttt{@Yelp.Restaurant, ...}

BERT (pretrained)

Do you have something cheap?

CONTEXT

QUESTION

contextual word embeddings

a sequence of vectors

a sequence of vectors
Remember This Image from Lecture 1?

Encoder-decoder with attention

Contextual word embeddings

Search: @Yelp.Restaurant, price == cheap & & ... 

Decoder: LSTM + Attention + pointer (autoregressive)

BiLSTM

CoAttention

Transformer

BERT (pretrained)

Search: @Yelp.Restaurant, ... 

CONTEXT

Do you have something cheap? 

QUESTION
Remember This Image from Lecture 1?

Search :@Yelp.Restaurant, price == cheap && ... →

Decoder: LSTM + Attention + pointer (autoregressive)

BiLSTM

CoAttention

Transformer

Search :@Yelp.Restaurant, ... →

CONTEXT

Do you have something cheap? →

BERT (pretrained)

encoder-decoder with attention

contextual word embeddings

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Remember This Image from Lecture 1?

Encoder-decoder with attention

Contextual word embeddings

Decoder: LSTM + Attention + pointer (autoregressive)

BiLSTM

CoAttention

Transformer

Search: @Yelp.Restaurant, price == cheap & & ...

Search: @Yelp.Restaurant, ...

CONTEXT

Do you have something cheap?

QUESTION

a sequence of vectors

a sequence of vectors
Practical Notes

• Python
• PyTorch
• Genie NLP
• HuggingFace’s transformers package includes state-of-the-art pre-trained language models like BERT