机器翻译

数据集 格式:

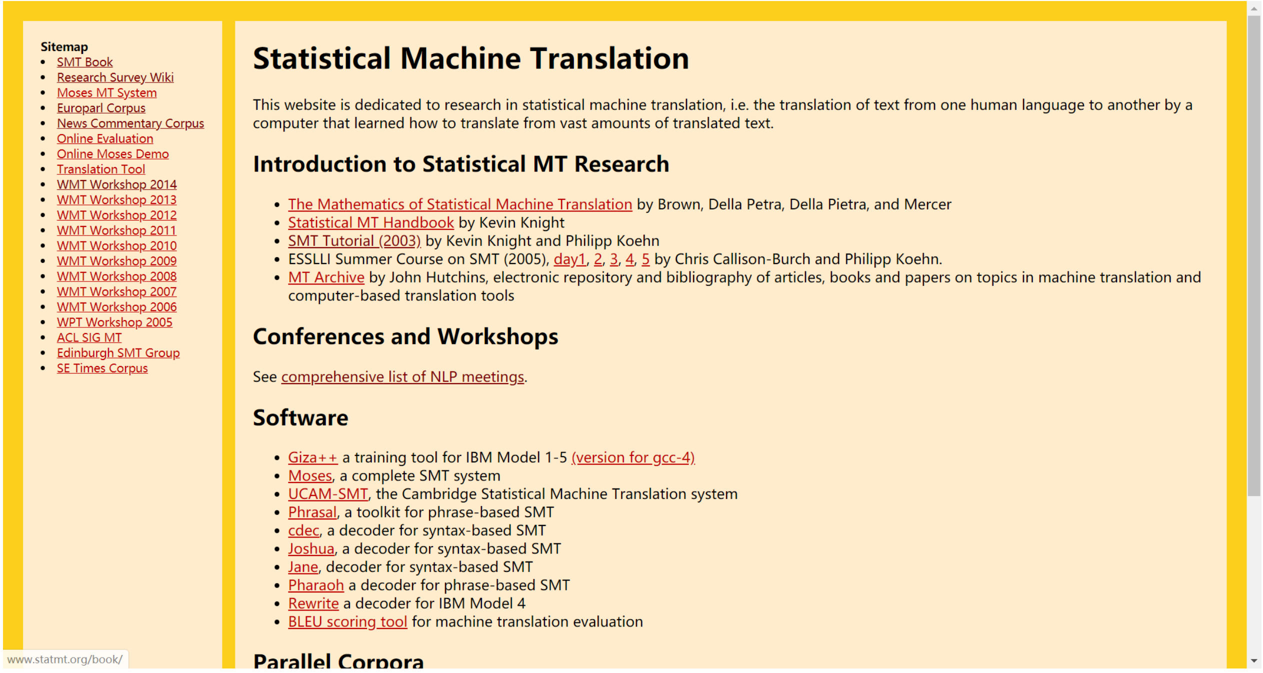
句子pairs:

$$\begin{array}{cc} english\ sentence_1 & chinese\ sentence_1 \\ english\ sentence_2 & chinese\ sentence_2 \\ english\ sentence_3 & chinese\ sentence_3 \\ & \cdots\cdots \\ english\ sentence_n & chinese\ sentence_n \end{array}$$

例子:

规模	源句子	目标句子	提供者	详情	备注
小规模	英语	越南语	IWSLT	133k sentence pairs	-
大规模	德语	英语	WMT	4.5M sentence pairs	-

WMT网站



Sitemap
- SMT Book
- Research Survey Wiki
- Moses MT System
- Europarl Corpus
- News Commentary Corpus
- Online Evaluation
- Online Moses Demo
- Translation Tool
- WMT Workshop 2014
- WMT Workshop 2013
- WMT Workshop 2012
- WMT Workshop 2011
- WMT Workshop 2010
- WMT Workshop 2009
- WMT Workshop 2008
- WMT Workshop 2007
- WMT Workshop 2006
- WPT Workshop 2005
- ACL SIG MT
- Edinburgh SMT Group
- SE Times Corpus

Statistical Machine Translation

This website is dedicated to research in statistical machine translation, i.e. the translation of text from one human language to another by a computer that learned how to translate from vast amounts of translated text.

Introduction to Statistical MT Research

- The Mathematics of Statistical Machine Translation by Brown, Della Petra, Della Pietra, and Mercer
- Statistical MT Handbook by Kevin Knight
- SMT Tutorial (2003) by Kevin Knight and Philipp Koehn
- ESSLLI Summer Course on SMT (2005), day1, 2, 3, 4, 5 by Chris Callison-Burch and Philipp Koehn.
- MT Archive by John Hutchins, electronic repository and bibliography of articles, books and papers on topics in machine translation and computer-based translation tools

Conferences and Workshops

See comprehensive list of NLP meetings.

Software

- Giza++ a training tool for IBM Model 1-5 (version for gcc-4)
- Moses, a complete SMT system
- UCAM-SMT, the Cambridge Statistical Machine Translation system
- Phrasal, a toolkit for phrase-based SMT
- cdec, a decoder for syntax-based SMT
- Joshua, a decoder for syntax-based SMT
- Jane, decoder for syntax-based SMT
- Pharaoh a decoder for phrase-based SMT
- Rewrite a decoder for IBM Model 4
- BLEU scoring tool for machine translation evaluation

Parallel Corpora

www.statmt.org/book/

数据集部分

ACL 2014 NINTH WORKSHOP
ON STATISTICAL MACHINE TRANSLATION

Shared Task: Machine Translation

26-27 June 2014
Baltimore, USA

[HOME] | [TRANSLATION TASK] | [METRICS TASK] | [QUALITY ESTIMATION TASK] | [MEDICAL TRANSLATION TASK] | [SCHEDULE] | [PAPERS] | [AUTHORS] | [RESULTS]

The recurring translation task of the WMT workshops focuses mainly on European language pairs, but this year we have introduced English-Hindi as an experimental, low resource language pair. Translation quality will be evaluated on a shared, unseen test set of news stories. We provide a parallel corpus as training data, a baseline system, and additional resources for download. Participants may augment the baseline system or use their own system.

GOALS

The goals of the shared translation task are:

- To investigate the applicability of current MT techniques when translating into languages other than English
- To examine special challenges in translating between European languages, including word order differences and morphology
- To investigate the translation of low-resource, morphologically rich languages
- To create publicly available corpora for machine translation and machine translation evaluation
- To generate up-to-date performance numbers for European languages in order to provide a basis of comparison in future research
- To offer newcomers a smooth start with hands-on experience in state-of-the-art statistical machine translation methods

We hope that both beginners and established research groups will participate in this task.

TASK DESCRIPTION

We provide training data for five language pairs, and a common framework (including a baseline system). The task is to improve methods current methods. This can be done in many ways. For instance participants could try to:

- improve word alignment quality, phrase extraction, phrase scoring
- add new components to the open source software of the baseline system
- augment the system otherwise (e.g. by preprocessing, reranking, etc.)

DOWNLOAD

- Parallel data:

File	Size	CS-EN	DE-EN	HI-EN	FR-EN	RU-EN	Notes
Europarl v7	628MB	✓	✓		✓		same as previous year, corpus home page
Common Crawl corpus	876MB	✓	✓		✓	✓	same as previous year
UN corpus	2.3GB				✓		same as previous year, corpus home page
News Commentary	77MB	✓	✓		✓	✓	updated, data with document boundaries
10^9 French-English corpus	2.3 GB				✓		same as previous year [md5|sha1]
CzEng 1.0	115MB	✓					same as previous year, corpus home page (avoid sections 98 and 99)
Yandex 1M corpus	121MB					✓	corpus home page; v1.3 now in original case
Wiki Headlines	7.8MB			✓		✓	Provided by CMU. The ru-en is unchanged from last year.
HindEnCorp	25MB			✓			Collected by Charles University
~~The JHU Corpus~~				~~✓~~			This is fully contained in HindEnCorp, so not made available here.

翻译系统

统计机器翻译

- **方法：**

将原句子分成短语块，查词典翻译

$$P(en \mid ch) = \frac{P(ch \mid en) * p(en)}{P(ch)}$$

P(ch)可以视为常数，写成：

$$P(en \mid ch) = argmax_{en} \quad P(ch \mid en) * P(en)$$

例子：

假如我们有语料库：

```
今天 是 个 好 天气。        Today is a fine day.
你 真是 太 可爱 了。        You are so cute.
你 今天 上午 有 课。        You have classes this morning.
接下来 有 很多 论文 要 读。  There are many papers to read next.
```

```
他 是个 爱 读书 的 孩子。    He is a child who likes reading.
是 时候 去 峡谷 乘凉 了。    It's time to cool down in the canyon.
亚瑟 就是 峡谷 中 的 王者。  Arthur is the king in the canyon.
这篇 论文 讲了 很多 模型，  This paper talks about a lot of models,
这些 模型 的 效果 很不错。  and the results of these models are very good.
```

翻译：我在 峡谷 中 读 论文。

$$
\begin{aligned}
P(en \mid ch) &= P(en \mid \text{“我 在 峡谷 中 读 论文”}) \\
&= P(\text{“我 在 峡谷 中 读 论文”} \mid w_1, w_2, w_3, w_4, w_5, w_6) * P(w_1, w_2, w_3, w_4, w_5, w_6) \\
&= A * B
\end{aligned}
$$

其中，可认为A是翻译模型，B是语言模型， B可以用来评价生成句子的质量：

$$
\begin{aligned}
&A = P(\text{“我”} \mid w_1)P(\text{“在”} \mid w_2)P(\text{“峡谷”} \mid w_3)P(\text{“中”} \mid w_4)P(\text{“读”} \mid w_5)P(\text{“论文”} \mid w_6) \\
&B = P(w_1, w_2, w_3, w_4, w_5, w_6) \\
&1) = P(w_1) * P(w_2) * P(w_3) * P(w_4) * P(w_5) * P(w_6) \qquad (unigram\text{形式}) \\
&2) = P(w_1) * P(w_2 \mid w_1) * P(w_3 \mid w_2) * P(w_4 \mid w_3) * P(w_5 \mid w_4) * P(w_6 \mid w_5) \qquad (bigram\text{形式}) \\
&3) = P(w_1) * P(w_2 \mid w_1) * P(w_3 \mid w_1, w_2) * P(w_4 \mid w_2, w_3) * P(w_5 \mid w_3, w_4) * P(w_6 \mid w_4, w_5) \qquad (trigram)
\end{aligned}
$$

B如何评价一个句子像不像人说的呢？我们为您B越大说明句子越像人话，事实上也是这样的，你可以计算下。1）形式的除外；将B写成对数和形式可以得到Perplex指标，越小句子越通顺。

- **缺点：**
  - 不流畅，无法利用语义信息；
  - 需要领域知识；
  - 计算耗时；

神经机器翻译(NMT)

1. 文本表示

我们需要将文本表示成数值(scalar/vector)形式，才能为给神经网络模型。历史上有很多将单词表示成向量的方法，他们各有优劣。

1.1 One-Hot Vector

假如我们的语料库只有一句话：

```
我 爱 北京 天安门 ， 他 也 爱。
```

则我们的词典有 $[\text{我，爱，北京，天安门，他，也，} <com>, <eos>]$ 8个单词，则上面句子可以表示成：

$$
\begin{aligned}
\text{"我"} \quad & [1,0,0,0,0,0,0,0] \\
\text{"爱"} \quad & [0,1,0,0,0,0,0,0] \\
\text{"北京"} \quad & [0,0,1,0,0,0,0,0] \\
\text{"天安门"} \quad & [0,0,0,1,0,0,0,0] \\
\text{"}<com>\text{"} \quad & [0,0,0,0,0,0,1,0] \\
\text{"他"} \quad & [0,0,0,0,1,0,0,0] \\
\text{"也"} \quad & [0,0,0,0,0,1,0,0] \\
\text{"爱"} \quad & [0,1,0,0,0,0,0,0] \\
\text{"}<eos>\text{"} \quad & [0,0,0,0,0,0,0,1]
\end{aligned}
$$

其中，每个词向量的维度都是 |V| (词典大小)

- 缺点

- 矩阵稀疏，维度大
- 无法表示单词的语义信息
- 没有使用上下文信息

1.2 BOW(bag of words)

一种基于词频的向量，假如我们有 $科技类docs1, 体育类docs2, 时政类docs3, 娱乐类docs4$，我们统计每类文档下面每个单词出现的次数：

words	docs1	docs2	docs3
我	10	3	30
汽车	50	10	2
...	...	...	...
中国	30	20	60

我们可以把每行拿出来代表这个单词的向量。

- 优点
  - 可以计算单词之间的相似性
  - 维度可以调整
- 缺点
  - 每个单词的词频有相同的重要性
  - 无法表示单词与单词之间的语义信息(上下文)
- 解决方法
  - tf-idf向量（解决每个文档中每个单词的重要性问题）（略）
  - word vector(利用上下文信息)

1.3 Word Embedding

1.3.1 使用语言模型（LM）训练

可以把语言模型裂解为评价一个句子像不像人说的话的模型；

$P(w_1, w_2, ..., w_n)$， 值越大越像人说的话。

1)神经网络语言模型(NNLM)

由前t-1个词预测下面一个单词(2003)：

$P(W_t = "some\_word" \mid W_1, W_2, ..., W_{t-1})$

2)Word2Vec

- CBOW

- 上下文预测中心词

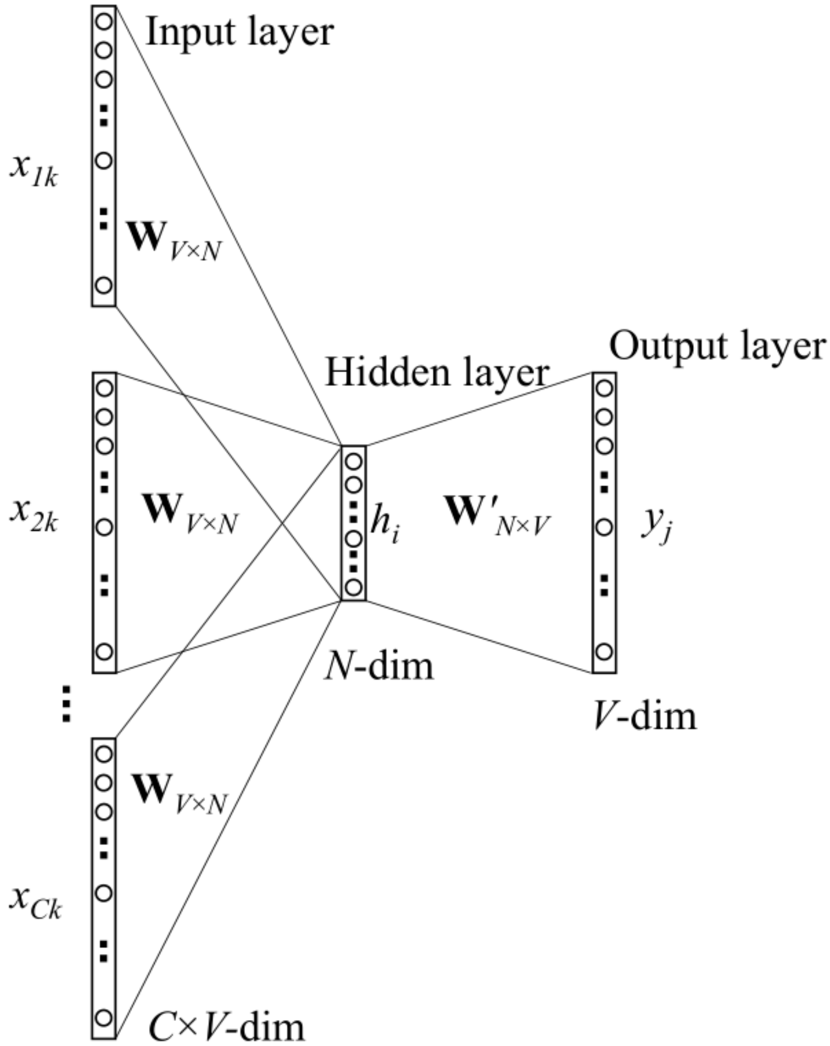


Figure 2: Continuous bag-of-word model

- Skip-gram

- 中心词预测上下文

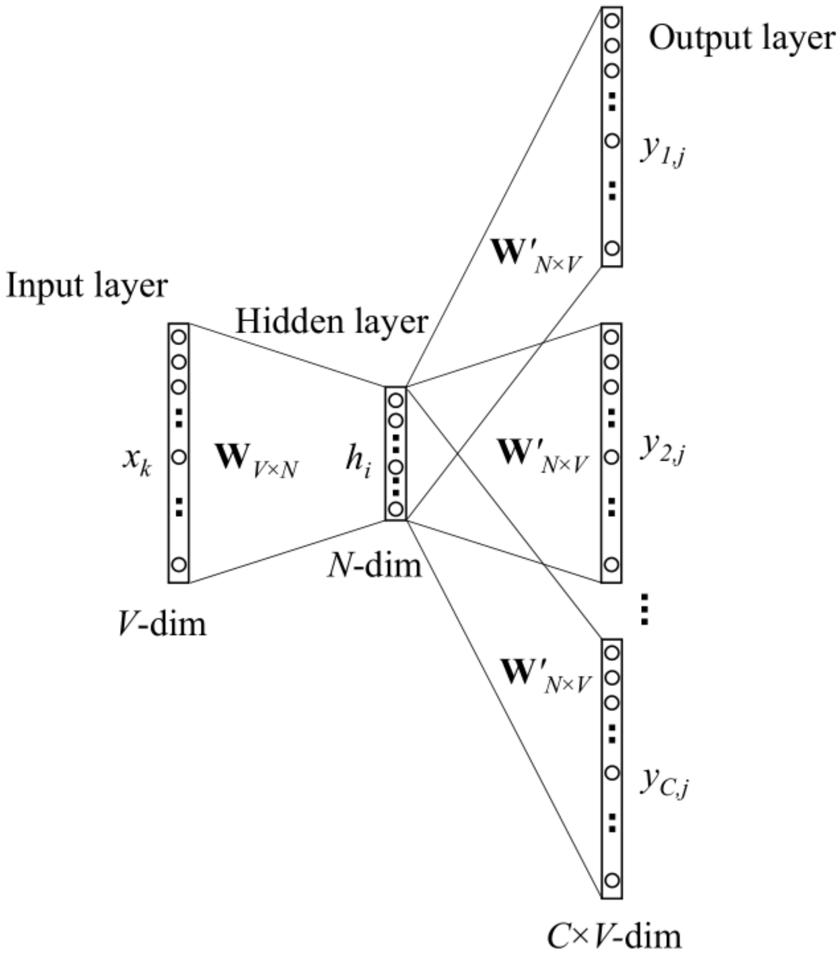


Figure 3: The skip-gram model.

- 优点
  - 利用单词之间的关系表示语义信息
  - 维度可控
- 缺点:
  - 多语义单词较难处理
- 解决方法 ELMo（RNN）, Bert（transformer）等预训练模型（略）

```
3）（Embedding from Language Models）ELMo

多层双向RNN训练

缺点：
     - RNN训练速度慢
     - 长时依赖信息很难提取

4）GPT

- transformer的decoder

5）Bert

- transformer的encoder
```

2. 翻译模型

神经机器翻译的整体框架目前主要是seq2seq模型，解决的是变长输入和变长输出的问题。

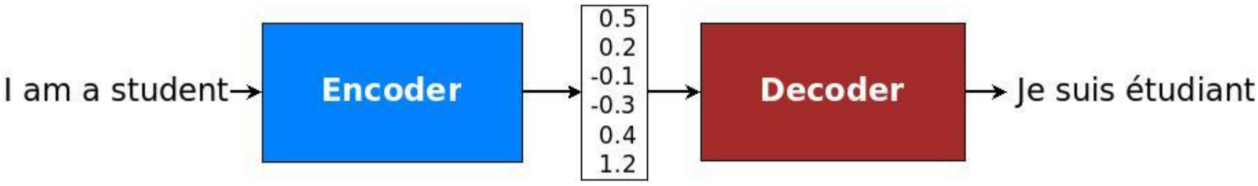
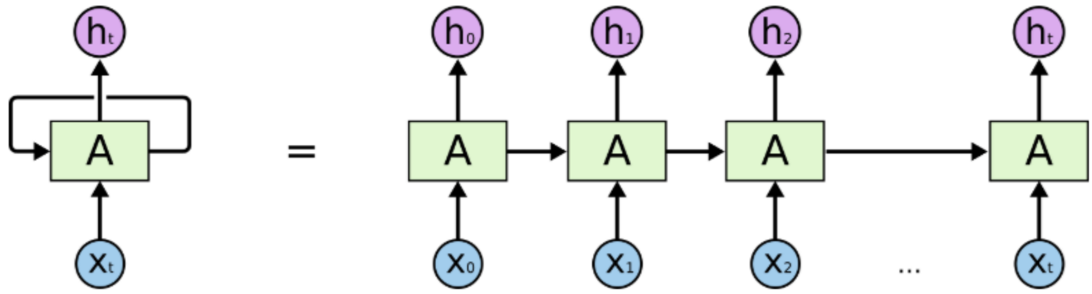


Figure 1. Encoder-decoder architecture *(源自： https://github.com/tensorflow/nmt#introduction)*

2.1 基于RNN的

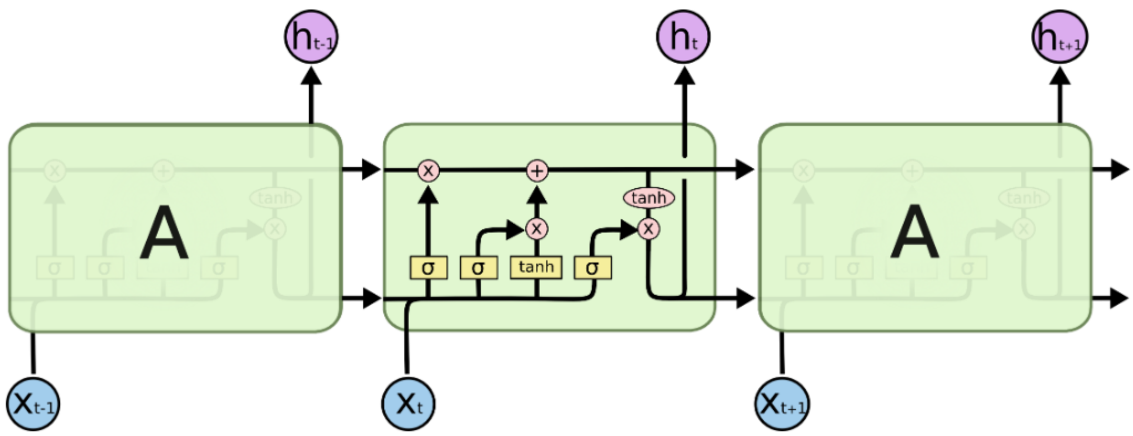
- 方法：通过RNN-encoder将源句子转化为一个vector(常成为这句话的contex vector)，再将该向量送入Decoder产生目标句子。

普通的RNN：



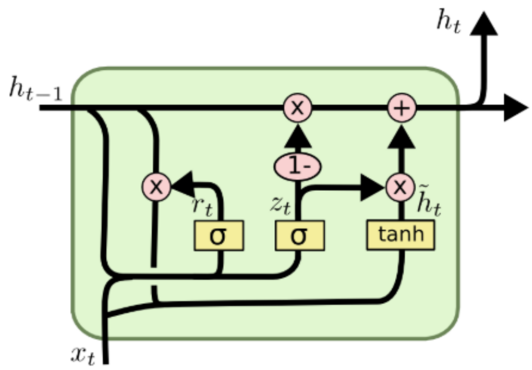
An unrolled recurrent neural network.

LSTM：



The repeating module in an LSTM contains four interacting layers.

GRU：



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- 整体框架

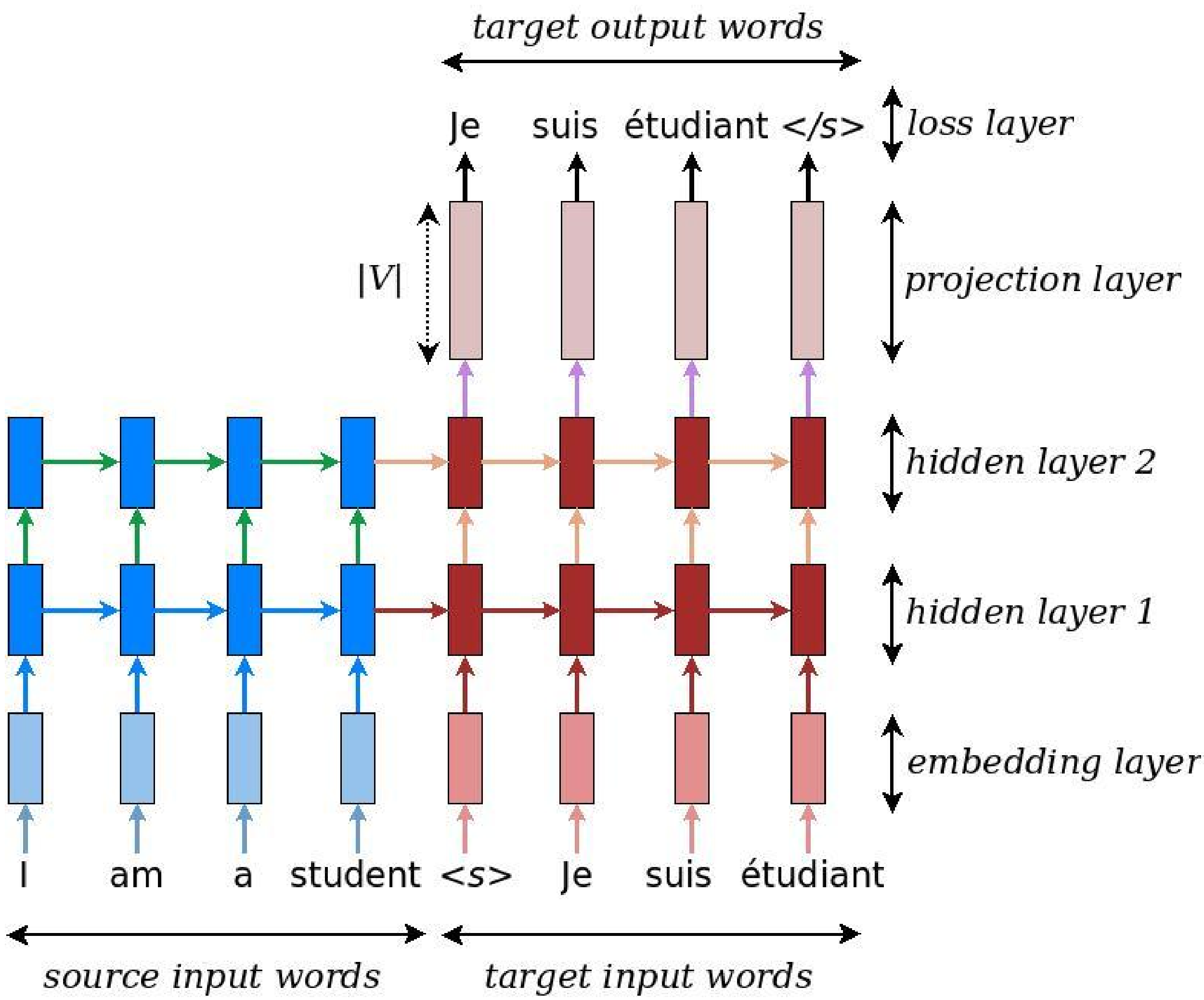


Figure 2. Neural machine translation

数据输入输出shape

以单向、多层LSTM的encoder-decoder模型为例，数据的输入/输出shape为：

- **encoder_inputs** [max_encoder_time, batch_size]: source input words
- **decoder_inputs** [max_decoder_time, batch_size]: target input words

- **decoder_outputs** [max_decoder_time, batch_size]: target output words

- **优点**： 利用了语义信息；能捕获较长依赖信息；翻译流利；
- **缺点**： 无法捕获更长的依赖；训练时间长；
- **类型**：
  - RNN's endocer-decoder
    - unidirectional/bidirectional rnn
    - depth - single/multi layer
    - type - vanilla RNN/LSTM/GRU(LSTM Networks)
  - attention machinism
    - 利用encoder的所有outputs，根据当前 w_t, h_t 计算每个encoder output 对应的权重，然后将encoder outputs加权求和，作为contex vector。

2.2 基于注意力机制的(self attention)

参考李宏毅课程PPT

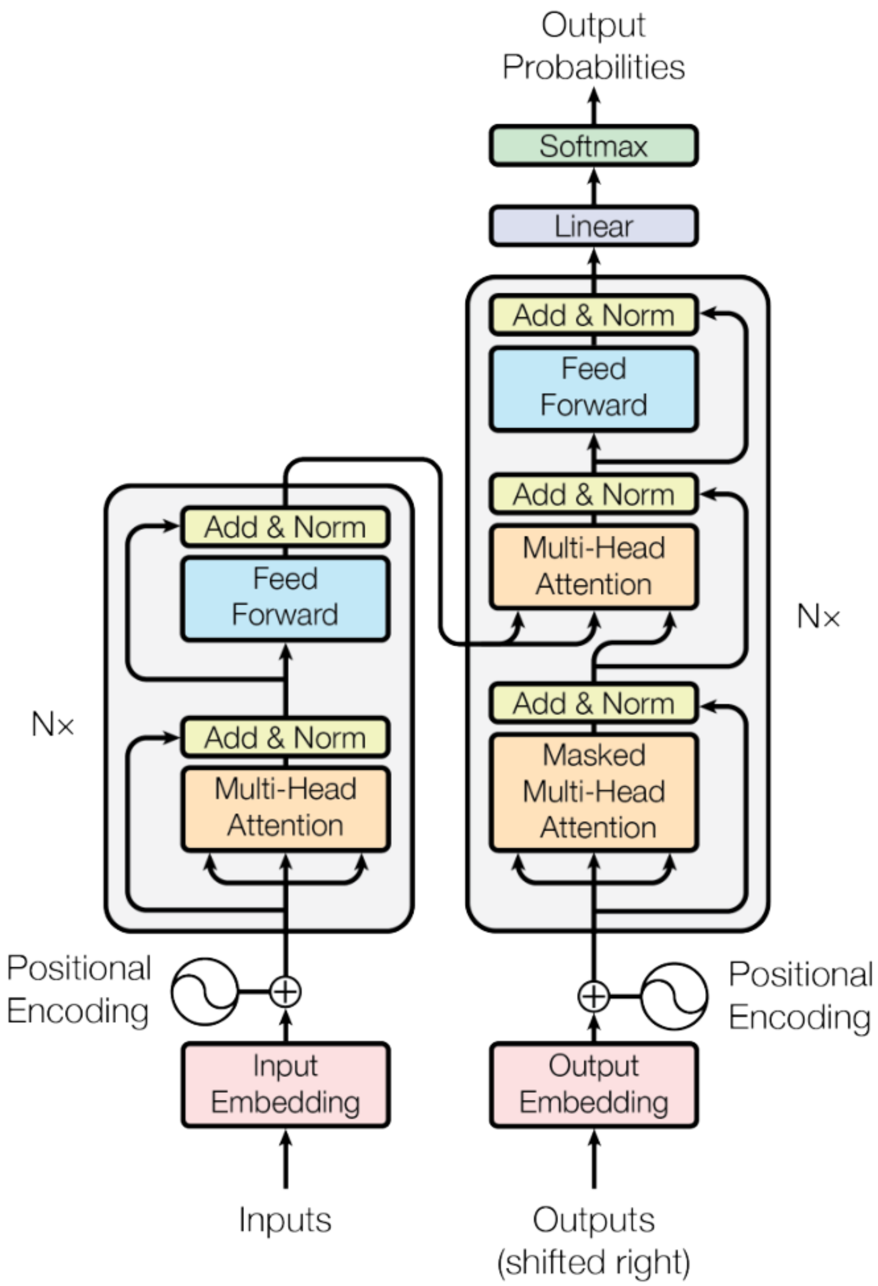


Figure 1: The Transformer - model architecture.

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2. https://jalammar.github.io/illustrated-transformer/
3. https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html#sphx-glr-intermediate-seq2seq-translation-tutorial-py
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5. https://github.com/tensorflow/nmt
6. http://colah.github.io/posts/2015-08-Understanding-LSTMs/
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