Attention-over-Attention Neural Networks for Reading Comprehension

Yiming Cui, Zhipeng Chen, Si Wei, Shijin Wang, Ting Liu

1、摘要

完型填空式的阅读理解是用于挖掘document和query之间的关系，这篇文章中，作者提出了一个全新的、简单的、有效的**attention-over-attention** 阅读理解模型，这个模型相比于其他 **attention** 模型，增加了一个 **attention** 层。模型的优点是简单，性能好。提出了一种 **N-best re-ranking** 策略用于二次验证候选集，提升了AoA模型的性能。实验结果表面，在CNN和CBT数据集上达到了最高的性能。

2、介绍

机器要阅读和理解人类语言非常困难，因为需要理解自然语言并且要分析其中的原因。阅读理解是一个非常常见的问题，通常是给定一个文本或者文章，以及相应的问题，需要机器正确的回答这个问题。最近，完型填空式的阅读理解问题变成一个非常流行的问题。

为了能够让机器更好的阅读理解，需要大量的有监督的训练数据集，Hermann et al. (2015)给出了CNN/Daily Mail数据集，不久之后这个作者又给出了CBT数据集，在这两个数据集下有很多人做过实验，他们大多数是建立的基于**attention**的神经网络，考虑document中的每个词对query的重要性。

作者这个模型在document层上面再加了一个 **attention**，前人的工作只是 query-to-document 方向的attention，作者在此基础上增加了一个 document-to-query 方向的 attention，作者认为主要的创新点在于：

- 在这个任务上第一次使用 attention-over-attention。
- 模型思想简单便于理解，性能更好。
- 提出了N-best re-ranking 策略对候选集重新打分，这个策略提升了整个模型的性能

3、完型填空式阅读理解

3.1、任务描述

完型填空任务可以描述为一个三元组

$$\langle D, Q, A \rangle$$

这个任务中，答案通常是文档中的一个单词，例如命名实体Obama，普通名词sunny，动词，介词。

3.2、存在的公开数据集

- CNN/Daily Mail 数据集的介绍

  这个数据集构建基本的思路是受启发于自动文摘任务，从两个大型的新闻网站CNN和Daily Mail中获取数据源，用abstractive的方法生成每篇新闻的summary，用新闻原文作为document，将summary中去掉一个entity作为query，被去掉的entity作为answer，从而得到阅读理解的数据三元组(document,query,answer)。

  这里存在一个问题，就是有的query并不需要联系到document，通过query中的上下文就可以predict出answer是什么，也就失去了阅读理解的意义，举个例子，蓝天白__。因此，论文中提出了用一些标识替换entity和重新排列的方法将数据打乱，防止上面现象的出现。处理之后的效果见下图：

	Original Version	**Anonymised Version**
Context		
	The BBC producer allegedly struck by Jeremy Clarkson will not press charges against the “Top Gear” host, his lawyer said Friday. Clarkson, who hosted one of the most-watched television shows in the world, was dropped by the BBC Wednesday after an internal investigation by the British broadcaster found he had subjected producer Oisin Tymon “to an unprovoked physical and verbal attack.” …	the *ent381* producer allegedly struck by *ent212* will not press charges against the “ *ent153* ” host , his lawyer said friday . *ent212* , who hosted one of the most - watched television shows in the world , was dropped by the *ent381* wednesday after an internal investigation by the *ent180* broadcaster found he had subjected producer *ent193* “ to an unprovoked physical and verbal attack . ” …
Query		
	Producer **X** will not press charges against Jeremy Clarkson, his lawyer says.	Producer **X** will not press charges against *ent212*, his lawyer says.
Answer		
	Oisin Tymon	*ent193*

- CBT 数据集介绍

  CBT的数据均来自Project Gutenberg，使用了其中的与孩子们相关的故事，这是为了保证故事叙述结构的清晰，从而使得上下文的作用更加突出。每篇文章只选用21句话，前20句作为document，将第21句中去掉一个词之后作为query，被去掉的词作为answer，并且给定10个候选答案，每个候选答案是从原文中随机选取的，并且这10个答案的词性是相同的，要是名词都是名词，要是命名实体都是实体，要是动词都是动词。作者通过实验发现，动词和介词与上下文关联不大，可以使用常识来进行判断，所以大部分的研究重点在于命名实体和普通名词。例子看下图：

"Well, Miss Maxwell, I think it only fair to tell you that you may have trouble with those boys when they do come. Forewarned is forearmed, you know. Mr. Cropper was opposed to our hiring you. Not, of course, that he had any personal objection to you, but he is set against female teachers, and when a Cropper is set there is nothing on earth can change him. He says female teachers can't keep order. He 's started in with a spite at you on general principles, and the boys know it. They know he'll back them up in secret, no matter what they do, just to prove his opinions. Cropper is sly and slippery, and it is hard to corner him."

"Are the boys big ?" queried Esther anxiously.

"Yes. Thirteen and fourteen and big for their age. You can't whip 'em -- that is the trouble. A man might, but they'd twist you around their fingers. You'll have your hands full, I'm afraid. But maybe they'll behave all right after all."

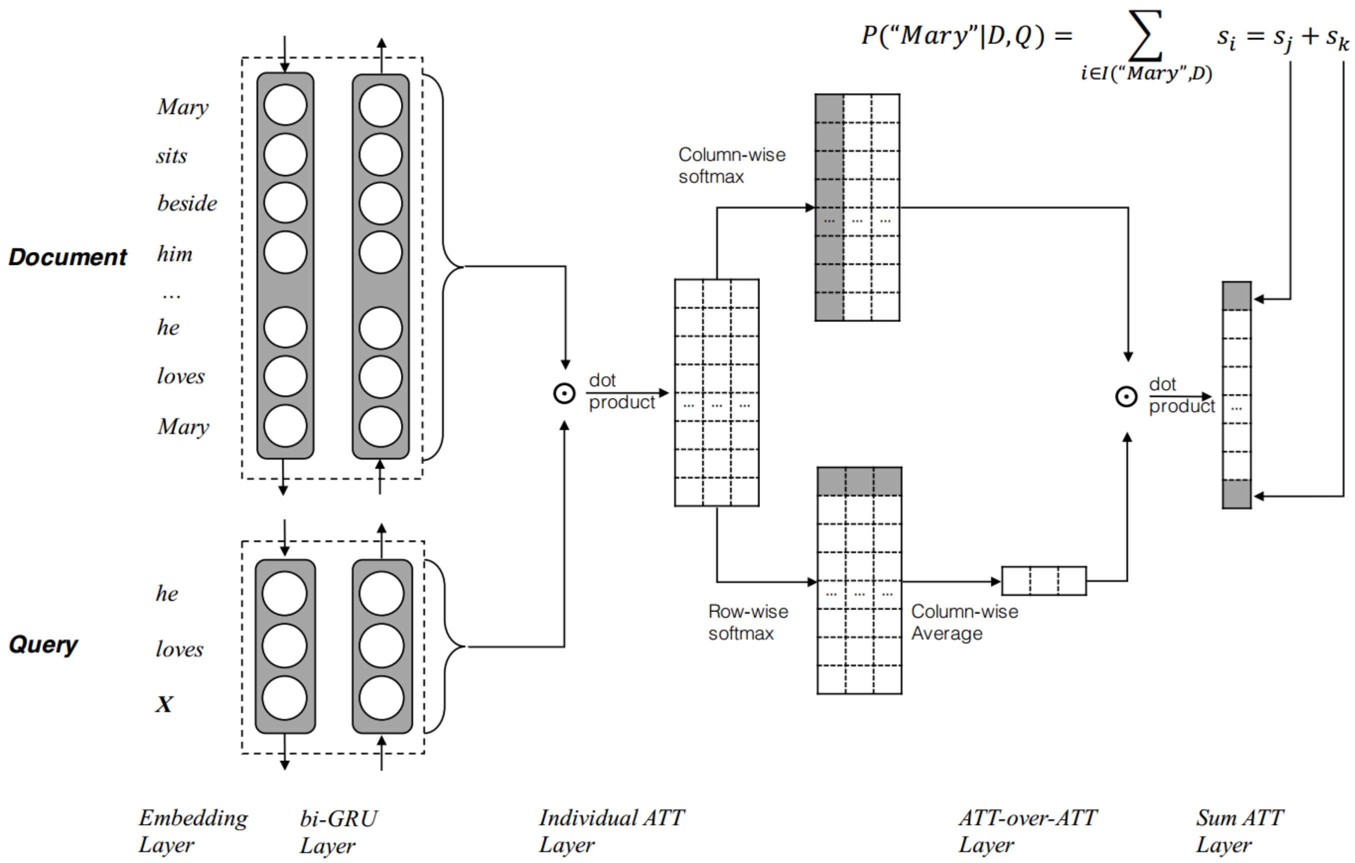
Mr. Baxter privately had no hope that they would, but Esther hoped for the best. She could not believe that Mr. Cropper would carry his prejudices into a personal application. This conviction was strengthened when he overtook her walking from school the next day and drove her home. He was a big, handsome man with a very suave, polite manner. He asked interestedly about her school and her work, hoped she was getting on well, and said he had two young rascals of his own to send soon. Esther felt relieved. She thought that Mr. Baxter had exaggerated matters a little.

```
S: 1 Mr. Cropper was opposed to our hiring you .
   2 Not , of course , that he had any personal objection to you , but he is set
   against female teachers , and when a Cropper is set there is nothing on earth can
   change him .
   3 He says female teachers ca n't keep order .
   4 He 's started in with a spite at you on general principles , and the boys know
   it .
   5 They know he 'll back them up in secret , no matter what they do , just to prove
   his opinions .
   6 Cropper is sly and slippery , and it is hard to corner him . ''
   7 `` Are the boys big ? ''
   8 queried Esther anxiously .
   9 `` Yes .
   10 Thirteen and fourteen and big for their age .
   11 You ca n't whip 'em -- that is the trouble .
   12 A man might , but they 'd twist you around their fingers .
   13 You 'll have your hands full , I 'm afraid .
   14 But maybe they 'll behave all right after all . ''
   15 Mr. Baxter privately had no hope that they would , but Esther hoped for the
   best.
   16 She could not believe that Mr. Cropper would carry his prejudices into a
   personal application .
   17 This conviction was strengthened when he overtook her walking from school the
   next day and drove her home .
   18 He was a big , handsome man with a very suave , polite manner .
   19 He asked interestedly about her school and her work , hoped she was getting on
   well , and said he had two young rascals of his own to send soon .
   20 Esther felt relieved .
q: She thought that Mr. ________ had exaggerated matters a little .
C: Baxter, Cropper, Esther, course, fingers, manner, objection, opinion, right, spite.
a: Baxter
```

- 两个数据集的统计信息

	CNN News			CBT NE			CBT CN		
	Train	Valid	Test	Train	Valid	Test	Train	Valid	Test
# Query	380,298	3,924	3,198	108,719	2,000	2,500	120,769	2,000	2,500
Max # candidates	527	187	396	10	10	10	10	10	10
Avg # candidates	26	26	25	10	10	10	10	10	10
Avg # tokens	762	763	716	433	412	424	470	448	461
Vocabulary		118,497			53,063			53,185	

4、Attention-over-Attention Reader 模型



4.1、Contextual Embedding

首先将document和query中的每个词提取出来，通过查询训练好的word embedding 得到每个词的特征表示。使用双向GRU模型来获取每个部分的语义表示。作者这里对每个单词的编码是384维，GRU输出层为256维。所以单个GRU的输入就是384维，输出为256维。双层GRU拼接之后的输出就是512维。

$$e(x) = W_e \cdot x，x\text{表示单词用}one - hot\text{表示}$$

$$\overrightarrow{h_s}(x) = \overrightarrow{GRU}(e(x))$$

$$\overleftarrow{h_s}(x) = \overleftarrow{GRU}(e(x))$$

$$h_s(x) = [\overrightarrow{h_s}(x); \overleftarrow{h_s}(x)]$$

这里假设 $h_{doc} \in R^{|D| \times 2d}$ 表示document部分输出的隐含状态矩阵。$h_{query} \in R^{|Q| \times 2d}$ 表示query部分输出的隐含状态矩阵。

4.2、Pair-wise Matching Score

计算 h_{doc} 中每个单词与 h_{query} 单词的匹配分数，得到分数矩阵。

$$M(i,j) = h_{doc}(i) \cdot h_{query}(j)^T$$

最后得到的分数矩阵 $M \in R^{|D| \times |Q|}$，上面的例子中document的维度是7×512，query的维度是 3×512，进行点乘之后变成了 7×3，列表示document中的单词，行表示query中的单词，AS Reader模型中，将query部分编码成 1×512，最后得到的也是 7×1 的矩阵。

4.3、Individual Attentions

计算query中每个词在document中注意力分布，使用softmax进行归一化，直观的解释就是**document**中每个词在**query**中的重要性，得到的矩阵的形状没有改变，只是数值进行了归一化。计算方法为：

$$\alpha(t) = softmax(M(1,t), \ldots, M(|D|,t))$$
$$\alpha = [\alpha(1), \alpha(2), \ldots, \alpha(|Q|)]$$

4.4、Attention-over-Attention

计算document中每个单词在query中注意力的权值分布，使用softmax归一化，直观的解释就是**query**中每个词在**document**中的重要性，然后在对每一列求平均，获取query中每个词在document中的权重，最直观的印象就是每个词在**query**中的权重。然后计算两个方向 attention 的点积，得到document中每个词在query中的重要性。

4.5、Final Predictions

通过上一步计算的每个词在query中的权重，让后将相同的词的概率相加，得到最终的概率，选择概率最大的值作为预测输出单词。整个模型的目标函数就是：

$$L = max \sum_i log(p(x))$$

5、N-best Re-ranking Strategy

从人的角度出发，我们做完型填空的时候，通常是先选择一个词，填入这个问句的空白出，然后再次验证这句话是否存在语法问题，是否流畅，是否是最合适的。如果存在问题，我们会尝试下一个选项。为了达到二次验证的目的，作者提出了N-best Re-ranking策略，来提升模型的性能。

- N-best Decoding
  相比于前面的选择一个概率最大的作为最后的答案，这里选择概率最大的N个单词作为候选词。

- Refill Candidate into Query
  把每个候选词填入Query中，检测他在里面的语义，形成N个句子。

- Feature Scoring
  对上面的N个句子进行评分，作者主要选择了三个评分特征。

  - Global N-gram LM:计算候选句子的流畅性。
    例如需要计算“我爱吃饭”和“我爱吃水”的流畅性，通过训练所以所有的文本可以得到已知“我爱吃”后面出现每个词的概率，这个概率就表示其流畅度。

  - Local N-gram LM:还是计算候选句子的流畅性，但是这次求概率时，不是计算所有的训练文本，而是从每个query对应的document来计算。这部分科可能会导致训练误差增加，但是可以提高泛化能，因为我们只需要从对应的原文中找，这在测试的时候是有利的，尤其是一些没有统计到的词。

  - Word-class LM:这个方法先将文档中所有单词，通过聚类的方法分为1000类，然后将候选句子中按照类别来计算流畅度，计算方法和Global N-gram LM相同。

- Weight Tuning
  通过训练数据不断的调整这三个特征的权重，使得目标损失最小。

- Re-scoring and Re-ranking
  计算每个句子在这三个特征下的加权评分，最后再次通过softmax选择概率最大的。

6、实验

6.1、实验设置

- Embedding层：embedding权重随机初始化
- 隐含层使用GRU随机初始化，主要参数设置如下图。
- 优化器使用ADAM，初始化的学习率为0.001，提取裁剪取值为5。
- N-best作者设置的N是5，选择5个作为候选集合。
- N-gram模型中，N设置为8。
- 集成模型使用的是4个最好的模型，使用不同的随机初始化种子得到的。

	Embed. # units	Hidden # units
CNN News	384	256
CBTest NE	384	384
CBTest CN	384	256

6.2、全部实验结果

	CNN News		CBTest NE		CBTest CN	
	Valid	Test	Valid	Test	Valid	Test
Deep LSTM Reader (Hermann et al., 2015)	55.0	57.0	-	-	-	-
Attentive Reader (Hermann et al., 2015)	61.6	63.0	-	-	-	-
Human (context+query) (Hill et al., 2015)	-	-	-	*81.6*	-	*81.6*
MemNN (window + self-sup.) (Hill et al., 2015)	63.4	66.8	70.4	66.6	64.2	63.0
AS Reader (Kadlec et al., 2016)	68.6	69.5	73.8	68.6	68.8	63.4
CAS Reader (Cui et al., 2016)	68.2	70.0	74.2	69.2	68.2	65.7
Stanford AR (Chen et al., 2016)	72.4	72.4	-	-	-	-
GA Reader (Dhingra et al., 2016)	73.0	73.8	74.9	69.0	69.0	63.9
Iterative Attention (Sordoni et al., 2016)	72.6	73.3	75.2	68.6	72.1	69.2
EpiReader (Trischler et al., 2016)	**73.4**	74.0	75.3	69.7	71.5	67.4
AoA Reader	73.1	**74.4**	**77.8**	**72.0**	**72.2**	**69.4**
AoA Reader + Reranking	-	-	**79.6**	**74.0**	**75.7**	**73.1**
MemNN (Ensemble)	66.2	69.4	-	-	-	-
AS Reader (Ensemble)	73.9	75.4	74.5	70.6	71.1	68.9
GA Reader (Ensemble)	76.4	77.4	75.5	71.9	72.1	69.4
EpiReader (Ensemble)	-	-	76.6	71.8	73.6	70.6
Iterative Attention (Ensemble)	74.5	75.7	76.9	72.0	74.1	**71.0**
AoA Reader (Ensemble)	-	-	**78.9**	**74.5**	**74.7**	70.8
AoA Reader (Ensemble + Reranking)	-	-	**80.3**	**75.6**	**77.0**	**74.1**

从实验结果可以发现，AoA模型在这两个数据集上面已经达到最佳的效果。上面一部分是单模型，下面一个是集成模型。

6.3、Effectiveness of Re-ranking Strategy

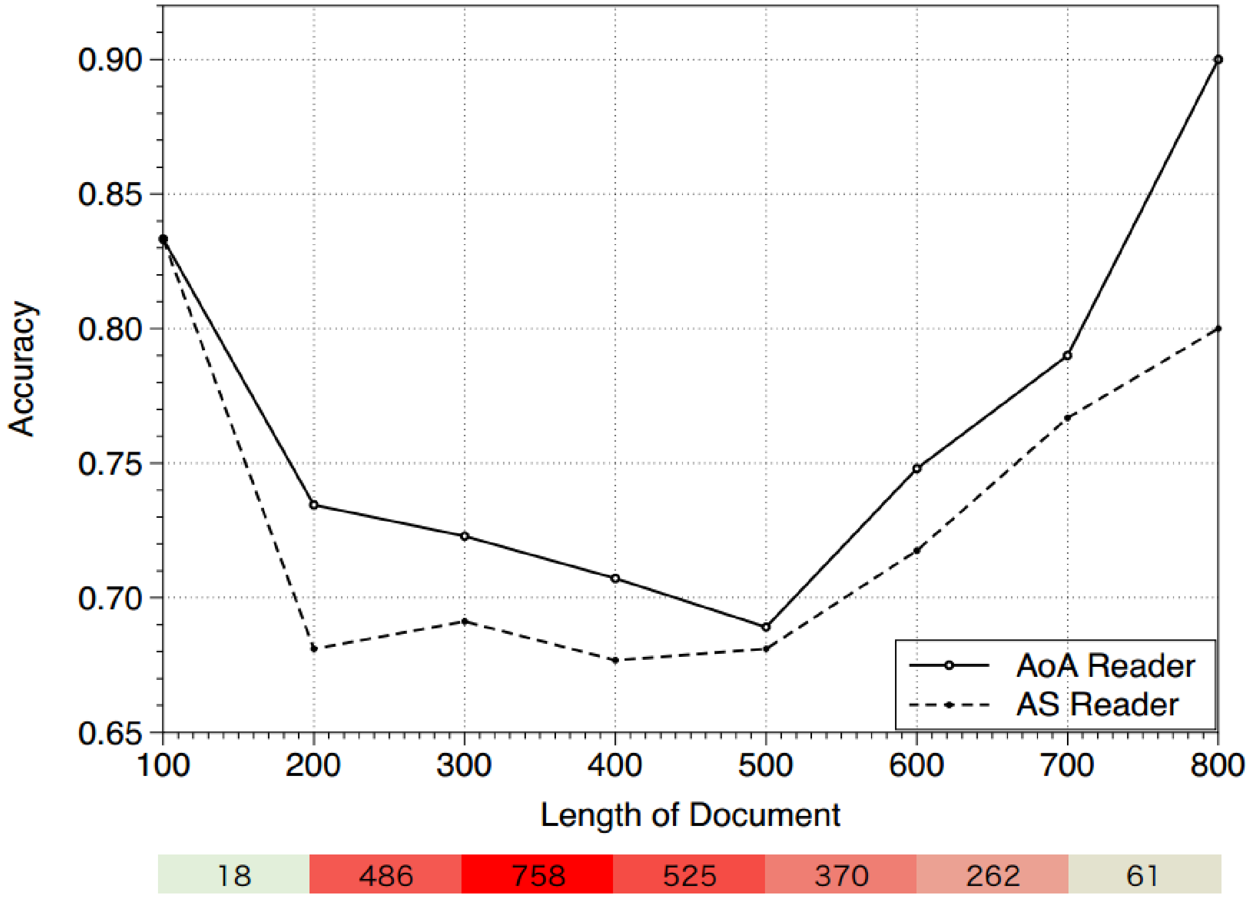
从上面的实验结果可以看出，Re-ranking对整个模型的效果有很多贡献。具体的贡献量如下：

	CBTest NE		CBTest CN	
	Valid	Test	Valid	Test
AoA Reader	77.8	72.0	72.2	69.4
+Global LM	78.3	72.6	73.9	71.2
+Local LM	79.4	73.8	74.7	71.7
+Word-class LM	79.6	74.0	75.7	73.1

- AoA Reader表示不使用Re-ranking策略的效果，每一行表示增加一个特征，并且累加以前的特征。
- 在CBT NE测试集上Global LM增加了0.6，Local LM增加了0.12，Word-class LM增加了0.2。
- 在CBT CN测试集上Global LM增加了1.8，Local LM增加了0.5，Word-class LM增加了1.4。
- 在NE这个数据集上，Local LM这个特征最为重要，回答问题的命名实体通常在对应的文章上。
- 在CN这个数据集上，Global LM和Word-class LM特征最为重要。

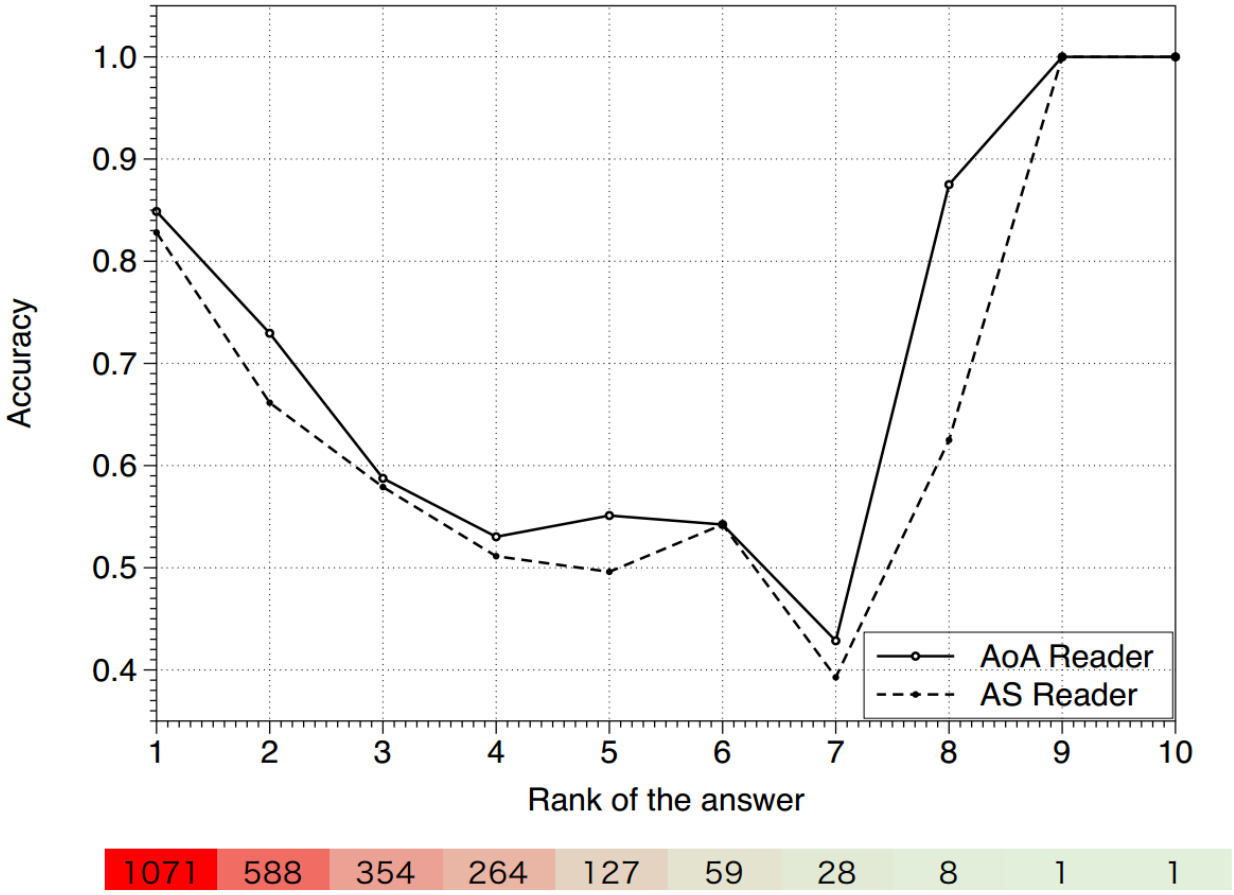
7、定量分析

- 在CBTNE上进行定量分析。下图是文档的长度和相应的精度的关系：



最下面的横条表示每个区间的文档的数量，可以看出文档单词个数在400-500之间，整个模型的效果最差。这个效果和AS Reader模型类似，当单词个数超过700时，AoA模型精度提升非常大，可以看出AoA模型比AS模型更适合阅读长文本。

- 下图表示测试精度与答案词频之间的关系：



最下面的横条表示有多少个问句选择了答案所在的词频。例如有1071个句子的答案选择了词频最高的作为答案，测试的准确率为0.85左右。