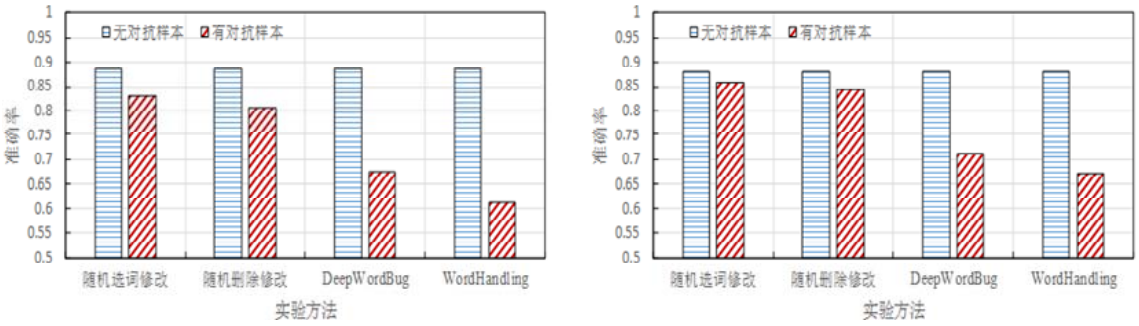


(a) LSTM 模型对比实验 (b) CNN 模型对比实验

Fig.6 Detection results of adversarial examples on Jingdong data in Table 2

图 6 表 2 中京东数据上对抗样本检测结果

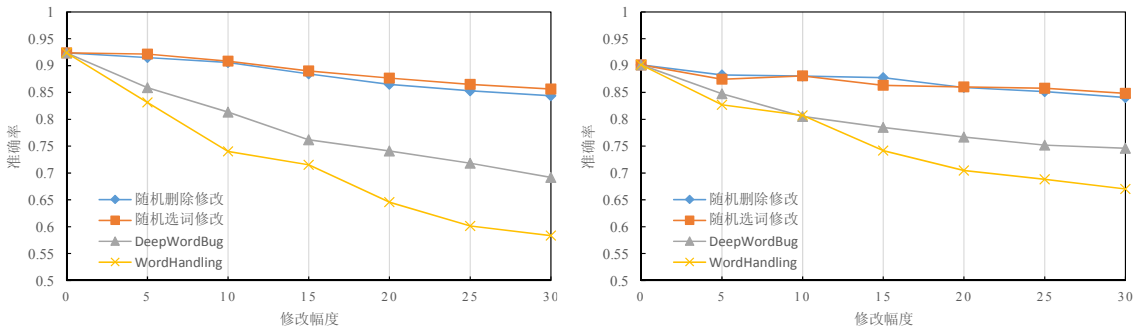
由表 2 可以看出,关键词语对输入数据类别倾向的影响较大,使用随机的方式对输入进行改动得到的结果并不理想;而且本文提出的 WordHandling 算法比 DeepWordBug 效果更佳.表 3 则是选取的若干原始样本和在其基础之上生成的对抗样本的例子,由表 3 可以看出,生成的对抗样本仍然能够通过语义上下文被人所理解,文本意思变化在可接受范围内.

Table 3 Examples of original examples and generated adversarial examples

表 3 原始样本和生成的对抗样本例子

原始样本:服务态度不好,换个房间都不给换,弄个最差的给住.	**负面评价**
对抗样本:服务态度部耗,换个房间都部给换,弄个醉岔的给住.	**正面评价**
原始样本:是非常不错的一家商务酒店,没有什么可以挑剔的了.	**正面评价**
对抗样本:是非常步挫的一家商务酒店,妹邮什么客衣跳题的了.	**负面评价**
原始样本:很一般,性价比很差.跟上海的快捷酒店相比,价格贵,服务差;窗户的高度太低,不小心会摔下去;令人匪夷所思的是,订的是大床房,但是床却是坏的;感觉很不好.	**负面评价**
对抗样本:很易班,性价比很岔.跟上海的快捷酒店相比,价格柜,服务岔;窗户的高度泰笛,不小心会摔下去;令人匪夷所思的是,订的是大床房,但是床却是踝的;感觉很部皓.	**正面评价**

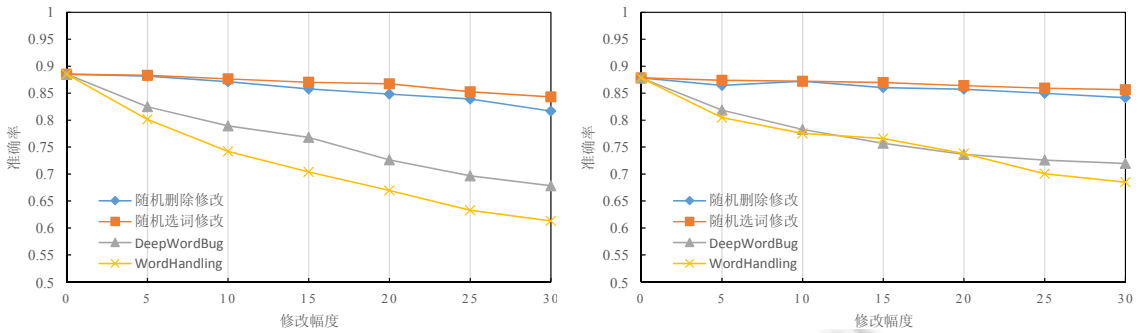
为了验证模型对于对抗样本检测的准确率与样本修改的幅度 m 的关联性,从两种数据集中分别选取 1 000 条长度大于 120 字的数据,根据不同的修改幅度生成相应的对抗样本.图 7 为携程酒店评论数据集在两种模型上检测的准确率随修改规模 m 变化的曲线,图 8 则是在京东购物评论数据集在两种模型上的实验结果.



(a) LSTM 模型对比实验 (b) CNN 模型对比实验

Fig.7 Change rate of accuracy of adversarial examples with the modified amplitude m on Ctrip data

图 7 携程数据对抗样本检测准确率随修改幅度 m 的变化曲线



(a) LSTM 模型对比实验 (b) CNN 模型对比实验

Fig.8 Change rate of accuracy of adversarial examples with the modified amplitude m on Jingdong data

图 8 京东数据抗样本检测准确率随修改幅度 m 的变化曲线

由图 7 和图 8 可以看出,随着修改规模 m 的增大,检测的准确率逐渐降低;即使仅对输入的数据进行个别重要词语的修改,本文提出的 WordHandling 算法也能生成许多对抗样本,误导检测系统的检测.而 m 次修改的总长度最多占输入数据长度的 1/6,超过该数值会严重影响文本的可读性,干扰人对对抗样本内容的理解.

4.3 对抗样本质量度量

图像中距离度量典型的方法是使用 L_p 范数,L_0,L_2,L_∞分别为 3 种常用的 L_p 范数,但其不适用于文本距离度量.因为图像是连续的,而文本是离散的且有词序限制.因此,本文采用 Word Mover's Distance(WMD)[41]对生成的对抗样本质量进行度量.WMD 基于 Earth Mover's Distance(EMD)[42],将 EMD 的适用范围扩展到自然语言处理领域,用于测量两文档之间的距离(即相似性).WMD 距离越大,两文档之间相似性越低;反之则越高.而文档越相似,其语义偏离度则越低.

从生成的对抗样本中随机选取 2 000 条数据进行实验,实验结果如图 9 所示.由该图可看出,WMD 距离小于 0.6 的对抗样本占实验样本总数量的 50%左右,这部分样本与原样本相似度较高;而 WMD 距离大于 0.8 的占样本总数量的 30%左右,这部分样本与原数据相似度较低.

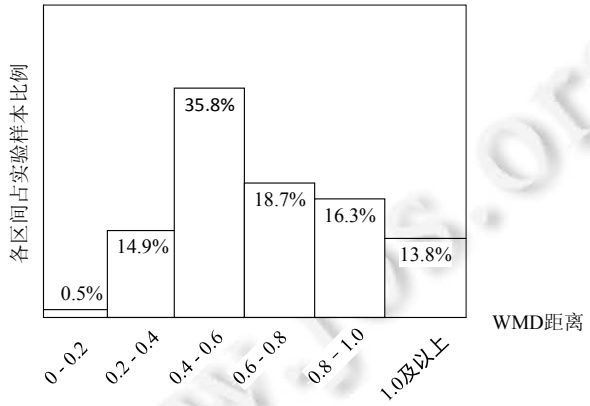


Fig.9 Ratio of sample numbers to total samples in different WMD distance intervals

图 9 不同 WMD 距离区间内样本数量占总样本的比例

对图 9 中各个区间的数据长度进行统计分析,结果见表 4.由该表可以看出,长度大于 30 的文本,在 WMD 距离偏小的区间内所占比例比短文本高.原因在于对抗样本生成过程中修改幅度大小 m,其影响被修改词语在整个输入数据中的比重,短文本数据即使只修改两三字,输入数据也被修改了 10%左右(以长度为 20 字的样本为

例).这也导致与相同修改幅度的长文本相比,短文本的可读性稍差.

Table 4 Proportion of long and short texts in different WMD distance intervals

表 4 不同 WMD 距离区间长短文本数量所占该区间比例

区间	样本长度小于 30(%)	样本长度大于 30(%)
0~0.4	15.4	84.6
0.4~0.6	20.9	79.1
0.6~0.8	24.7	75.3
0.8 及以上	58.1	41.9

表 5 中则给出了几例 WMD 距离计算实例.本文中,与原样本之间 WMD 距离小于 0.6 的对抗样本是语义偏离度较小,阅读性比较好的对抗样本.

Table 5 Examples of WMD distance calculation

表 5 WMD 距离计算实例

样本数据		WMD 距离
原始样本:很一般,性价比很差.跟上海的快捷酒店相比,价格贵,服务差;窗户的高度太低,不小心会摔下去;令人匪夷所思的是,订的是大床房,但是床却是坏的;感觉很不好. 对抗样本:很易班,性价比很岔.跟上海的快捷酒店相比,价格柜,服务岔;窗户的高度泰笛,不小心会摔下去;令人匪夷所思的是,订的是大床房,但是床却是踝的;感觉很部皓.	负面评价 正面评价	0.2196615
原始样本:屏幕较差,拍照也很粗糙. 对抗样本:屏幕交叉,拍照也很出操.	负面评价 正面评价	0.4243181
对抗样本:很易班,性价比很岔.跟上海的快捷酒店相比,价格柜,服务岔;窗户的高度泰笛,不小心会摔下去;令人匪夷所思的是,订的是大床房,但是床却是踝的;感觉很部皓. 对抗样本:屏幕交叉,拍照也很出操.		1.6947902
原始样本:很一般,性价比很差.跟上海的快捷酒店相比,价格贵,服务差;窗户的高度太低,不小心会摔下去;令人匪夷所思的是,订的是大床房,但是床却是坏的;感觉很不好. 原始样本:屏幕较差,拍照也很粗糙.		1.3644687

5 总 结

在本文中,我们提出了中文文本类型的对抗样本生成算法,以此来实现针对网络中深度学习模型的黑盒攻击,诱导这些检测系统做出错误的倾向性判别,使得制作的对抗样本能够避开检测,降低检测的准确率.本文首先利用设计的词语重要性计算函数计算文本数据中的各个词或词组的重要程度,并以此为依据进行排序,针对排在前 m 的词或词组,用同音词替换原词来生成对抗样本,方法有效,且生成的对抗样本内容的改变很小,仍然能够通过上下文或语音谐音来理解语句意思.实验结果表明,本文提出的 WordHandling 算法能够使 LSTM 模型对生成的对抗样本检测的准确率平均降低 29%,使 CNN 模型检测准确率平均降低 22%,且对原始的中文文本的修改幅度仅占输入数据长度的 14.1%.同时,对生成的对抗样本质量进行度量,保证语义偏离度小、可读性好,证明本文提出的 WordHandling 算法有效且表现较佳.此外,文中计算词的重要程度的词语重要性计算函数还能进一步优化,针对每个输入文本,修改幅度 m 的最优选取问题也存在提升的空间.在今后的工作中,我们会对这些存在问题解析并改善提高,并对能够进行定向分类的对抗样本生成进行研究.

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