

Sentiment Analysis of Turtle Books: A 439/539 NLP Project

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Abstract

The abstract should be approximately 100 words, and outline the problem (1-sentence), the specific task you're working on (1-sentence), your proposed approach/solution to the task (1 to 2 sentences), and your results (1-sentence). *Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetur adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.*

1 Introduction

The introduction should describe the problem area that you're working on in high-level general terms and it's utility, identify that gap in knowledge/the need, and then how you address that need.

For example: Sentiment analysis aims to automatically identify whether a piece of text is describing generally positive, neutral, or negative emotion (*the high-level description*). Sentiment analysis has broad utility, for example in automatically determining whether natural language comments left by consumers on online shopping platforms are expressing positive or negative emotion about particular products. Automatically analyzing the sentiment of products can help shopping platforms identify new products with positive reviews that could be highlighted to increase sales, or allow manufacturers to quickly sift through a large number of product reviews to identify potential areas of improvement *the utility of working on the task*.

Currently, there is *gap in knowledge*, for example, lack of sentiment analysis for a particular sub-domain (e.g. books about turtles). In this work, we collect a dataset of 200 reviews of turtle books and

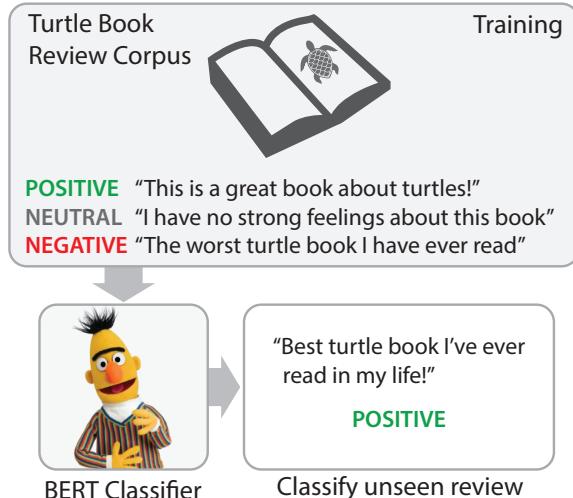


Figure 1: An example of the sentiment analysis task. A corpus of turtle book reviews serves as training data to fine-tune a BERT classification model, trained to classify reviews as *positive*, *neutral*, or *negative*. The classifier is then evaluated on unseen reviews.

provide human labels of their sentiment. We then train a XYZ model using this dataset, showing that we can reach an overall performance of XX% for this important task (*how you address the need/the contribution*). See Figure 1 for an example.

The Introduction is typically 1-1.5 pages (i.e. may spill onto the first column of the second page). The total length of your paper should follow the guideliens for a short ACL paper – 4 pages, plus additional pages for references. 539 students may use 4 or 5 pages.

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080 vestibulum turpis. Pellentesque cursus luctus mau-
081 ris.

082 2 Related Work

083 In this section, provide a brief review of 3 papers
084 that are related to your task. Normally, this is where
085 you review the state-of-the-art in this subfield or
086 task, and briefly contrast it with your approach.
087 Here, you just need to identify 3 paper that are in
088 the same area, and describe how they frame the
089 task, what methods they use, and their main results.
090 Citations should be entered into the custom.bib
091 file, and cited using the appropriate latex citation
092 commands, e.g. \cite{.

093 Aho et al. (1972) provided the first detailed study
094 of sentiment analysis on turtle book reviews, where
095 they use model XYZ on an in-house dataset of 50
096 turtle book reviews. Compared to Aho et al. (1972),
097 this work includes larger training evaluation, and
098 uses fancy model 2.0 that improves ABC.

099 Several groups have been interested in senti-
100 ment analysis on non-turtle books (e.g. Chandra
101 et al., 1981; Gusfield, 1997). For example, Ando et
102 al. (2005) explore the related task of sentiment anal-
103 ysis on near-domain books such as lizard books,
104 and pamphlets describing other reptiles. etc.

105 The related work should be approximately half
106 a page.

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124 dignissim rutrum.

125 3 Approach

126 How do you frame the problem? Classification,
127 ranking, sequence2sequence, etc? Do you need a
128 figure to describe the actual task? What are the
129 important things to know about your task? e.g. if
130 it's classification, how many classes?

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147 *sagittis quis, diam. Duis eget orci sit amet orci*
148 *dignissim rutrum.*

149 3.1 Data collection

150 Did you collect and/or label your own data for this
151 task? Describe the collection and labeling proce-
152 dure here. Provide one or two examples, possibly
153 in a figure.

154 Did you use someone elses data? Describe it,
155 and provide one or two examples, possibly in a
156 figure.

157 How is the data divided into train/dev/test sets?
158 (e.g. 50% / 25% / 25%)?

159 *Nam dui ligula, fringilla a, euismod sodales, sol-*
160 *licitudin vel, wisi. Morbi auctor lorem non justo.*

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3.2 Experiments

We evaluate the performance of XX models. Performance is measured using (*How is your task evaluated? Accuracy? F1? Precision@1? etc.*).

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3.3 Models

If you are doing an experimental paper, you must implement at least two models. One model should be a “baseline” model – a simple model that shows how well a simple method performs on the task. Typically these are n-gram models (e.g. your unigram/bigram model using logistic regression from Assignment 2), ranking using tf.idf vectors, etc.

Model XYZ: Succinctly describe the workings of your baseline model here. What features does it use? What learning framework does it use? etc. Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Model	Precision	Recall	F1
Baseline (Unigram+Bigram)	50	40	20
Fancy Model 2.0	60	50	30 [†]

Table 1: Task performance across the models under investigation. [†] signifies that performance is significantly different from baseline performance ($p < 0.05$) using a non-parametric bootstrap resampling test.

Model ABC: Succinctly describe the workings of your other fancy model here. For example, we make use of a BERT-based classifier (Devlin et al., 2018) fine tuned to perform the sentiment analysis task. For computational tractability we make use of the TinyBERT (Jiao et al., 2020) classifier, which reduces BERT from a 110M parameter model to a XXM parameter model with reduced computational requirements, while retaining much of the performance benefits of the original model. Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

3.4 Hyperparameter Tuning

You should report performance on both the **development** and **test** sets in your tables/figures, and describe any hyperparameters that were tuned on the development set.

3.5 Results

The experiments are described in Table 1. Overall the results show...

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255 dignissim rutrum.

256 3.6 Error Analysis

257 Students enrolled in 539 must complete an error
258 analysis (and extend their papers into an additional
259 page, to 5 pages). Analyze 50-100 randomly picked
260 errorful predictions that the model makes (on the
261 development set), and distill them into a number
262 of specific categories. Those are shown in Table 2
263 and described below.

264 **Complex Examples (50%):** Nam dui ligula, frin-
265 gilla a, euismod sodales, sollicitudin vel, wisi.
266 Morbi auctor lorem non justo. Nam lacus libero,
267 pretium at, lobortis vitae, ultricies et, tellus. Do-
268 nec aliquet, tortor sed accumsan bibendum, erat
269 ligula aliquet magna, vitae ornare odio metus a mi.
270 Morbi ac orci et nisl hendrerit mollis. Suspendisse
271 ut massa. Cras nec ante. Pellentesque a nulla. Cum
272 sociis natoque penatibus et magnis dis parturient
273 montes, nascetur ridiculus mus. Aliquam tincidunt
274 urna. Nulla ullamcorper vestibulum turpis. Pellen-
275 tesque cursus luctus mauris.

276 **Low frequency words (10%):** Nam dui ligula,
277 fringilla a, euismod sodales, sollicitudin vel, wisi.
278 Morbi auctor lorem non justo. Nam lacus libero,
279 pretium at, lobortis vitae, ultricies et, tellus. Do-
280 nec aliquet, tortor sed accumsan bibendum, erat
281 ligula aliquet magna, vitae ornare odio metus a mi.
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286 urna. Nulla ullamcorper vestibulum turpis. Pellen-
287 tesque cursus luctus mauris.

288 **Sarcasm (5%):** Nam dui ligula, fringilla a, eui-
289 smod sodales, sollicitudin vel, wisi. Morbi auctor
290 lorem non justo. Nam lacus libero, pretium at,
291 lobortis vitae, ultricies et, tellus. Donec aliquet,
292 tortor sed accumsan bibendum, erat ligula aliquet
293 magna, vitae ornare odio metus a mi. Morbi ac
294 orci et nisl hendrerit mollis. Suspendisse ut massa.
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297 nascetur ridiculus mus. Aliquam tincidunt urna.
298 Nulla ullamcorper vestibulum turpis. Pellen-
299 tesque cursus luctus mauris.

Prop.	Error Class
50%	Complex examples with ambiguous words
10%	Unseen data has low-frequency words
5%	Examples contain sarcasm
...	

Table 2: Common error classes and proportions of errors for 100 randomly selected errors on the development set.

300 4 Conclusion

301 A short summary paragraph (generally up to one
302 third of one column) summarizing the results. Nam
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313 tesque cursus luctus mauris.

314 5 Project Site

The project is available at <http://www.github.com/...>

317 References

- 318 Alfred V. Aho and Jeffrey D. Ullman. 1972. *The Theory
319 of Parsing, Translation and Compiling*, volume 1.
320 Prentice-Hall, Englewood Cliffs, NJ.
- 321 Rie Kubota Ando and Tong Zhang. 2005. A framework
322 for learning predictive structures from multiple tasks
323 and unlabeled data. *Journal of Machine Learning
324 Research*, 6:1817–1853.
- 325 Ashok K. Chandra, Dexter C. Kozen, and Larry J. Stock-
326 meyer. 1981. **Alternation**. *Journal of the Association
327 for Computing Machinery*, 28(1):114–133.
- 328 Jacob Devlin, Ming-Wei Chang, Kenton Lee, and
329 Kristina Toutanova. 2018. Bert: Pre-training of deep
330 bidirectional transformers for language understand-
331 ing. *arXiv preprint arXiv:1810.04805*.
- 332 Dan Gusfield. 1997. *Algorithms on Strings, Trees and
333 Sequences*. Cambridge University Press, Cambridge,
334 UK.
- 335 Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao
336 Chen, Linlin Li, Fang Wang, and Qun Liu. 2020.
337 Tinybert: Distilling bert for natural language under-
338 standing. In *Findings of the Association for Compu-
339 tational Linguistics: EMNLP 2020*, pages 4163–4174.

340

A Example Appendix

341

This is an appendix.