



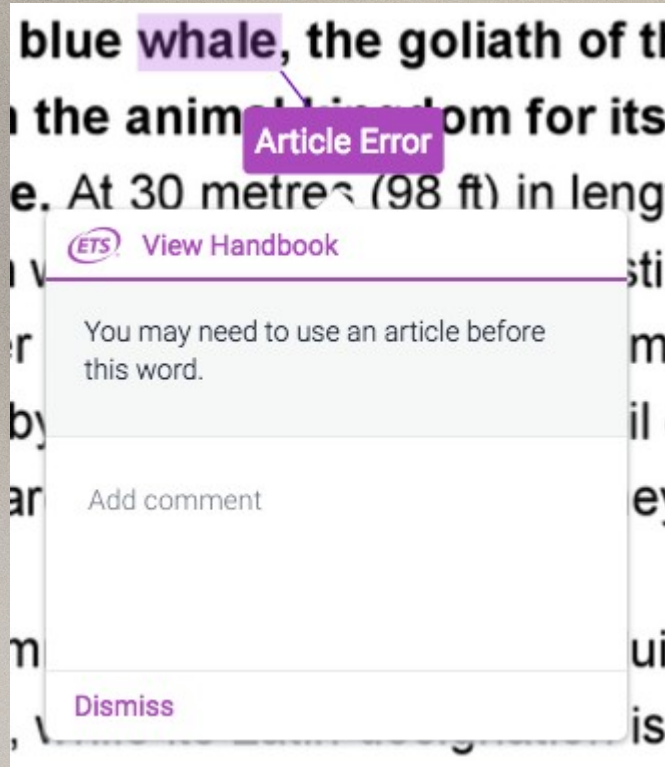
Automated Essay Scoring

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DSI-11 Capstone project

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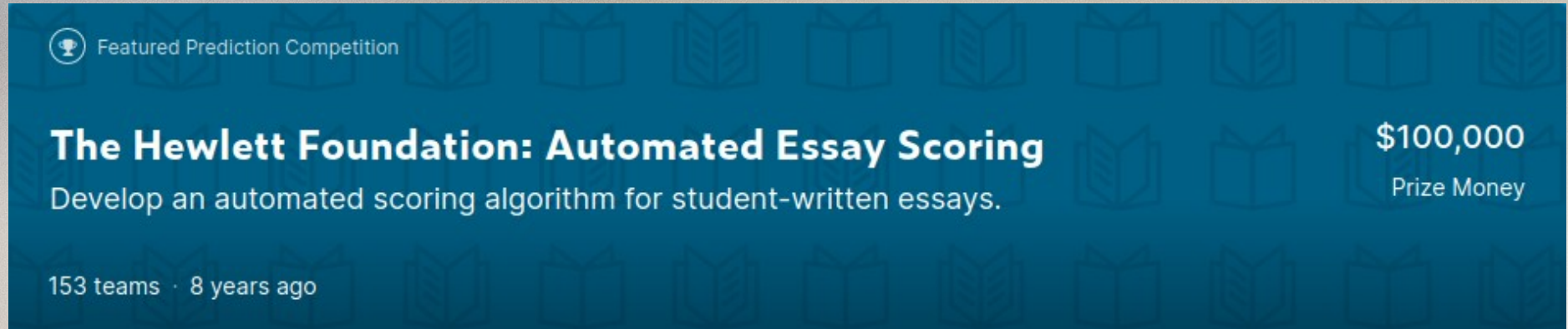
In 1999, ETS began using *e-rater*, which is now used to grade the SAT essay, along with a human reader.



Opponents of AES systems often try to game them; this essay, despite earning a top score, is filled with usage errors, contradictions, and non sequiturs:

I live in a luxury dorm. In reality, it costs no more than rat infested rooms at a Motel Six. The best minds of my generation were destroyed by madness, starving hysterical naked, and publishing obscene odes on the windows of the skull. Luxury dorms pay for themselves because they generate thousand and thousands of dollars of revenue. In the Middle Ages, the University of Paris grew because it provided comfortable accommodations for each of its students, large rooms with servants and legs of mutton. Although they are expensive, these rooms are necessary to learning.

In 2012, the Hewlett Foundation released ASAP,*
a dataset of 13,000 middle- & high-school essays.

A blue banner with a repeating book icon pattern. It contains text about a Kaggle competition. On the left, a trophy icon is next to the text 'Featured Prediction Competition'. The main title 'The Hewlett Foundation: Automated Essay Scoring' is in large white font, followed by the description 'Develop an automated scoring algorithm for student-written essays.' in smaller white font. On the right, '\$100,000' is displayed in large white font, with 'Prize Money' below it in smaller white font. At the bottom left, '153 teams · 8 years ago' is written in white.

Featured Prediction Competition

The Hewlett Foundation: Automated Essay Scoring

Develop an automated scoring algorithm for student-written essays.

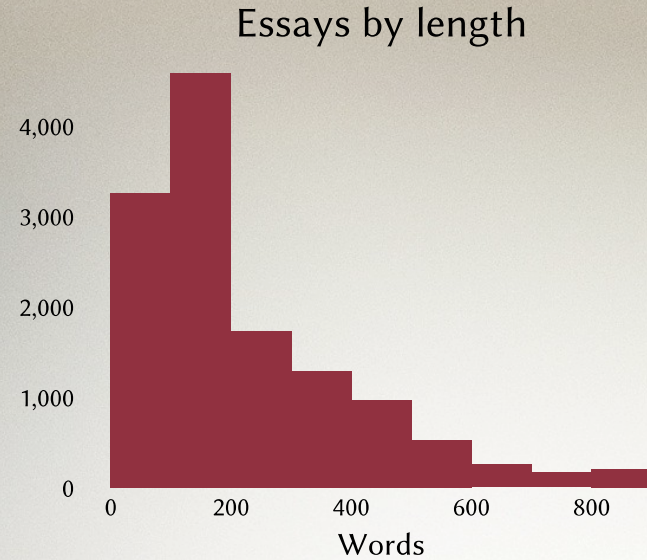
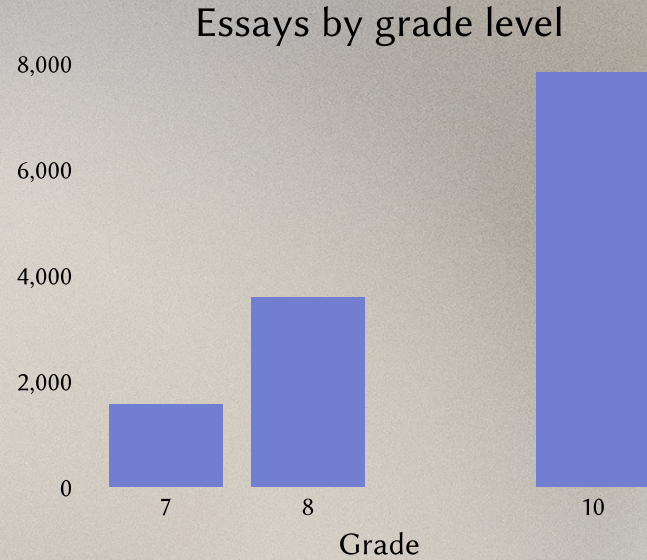
\$100,000
Prize Money

153 teams · 8 years ago

* Automated Student Assessment Prize

kaggle.com/c/asap-aes

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Set	Grade level	Style	Score range
1	8	Persuasion	2–12
2	10	Persuasion	1–6, 1–4
3	10	Exposition	0–3
4	10	Exposition	0–3
5	8	Exposition	0–4
6	10	Exposition	0–4
7	7	Narrative	0–30
8	10	Narrative	0–60

My training set: the ~3,500 essays in sets 3 & 4, which are comparable but topically different.

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5	8	Exposition	0–4
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We want an essay scorer to take into account:

Completion

Structure

Relevance

Grammatical correctness

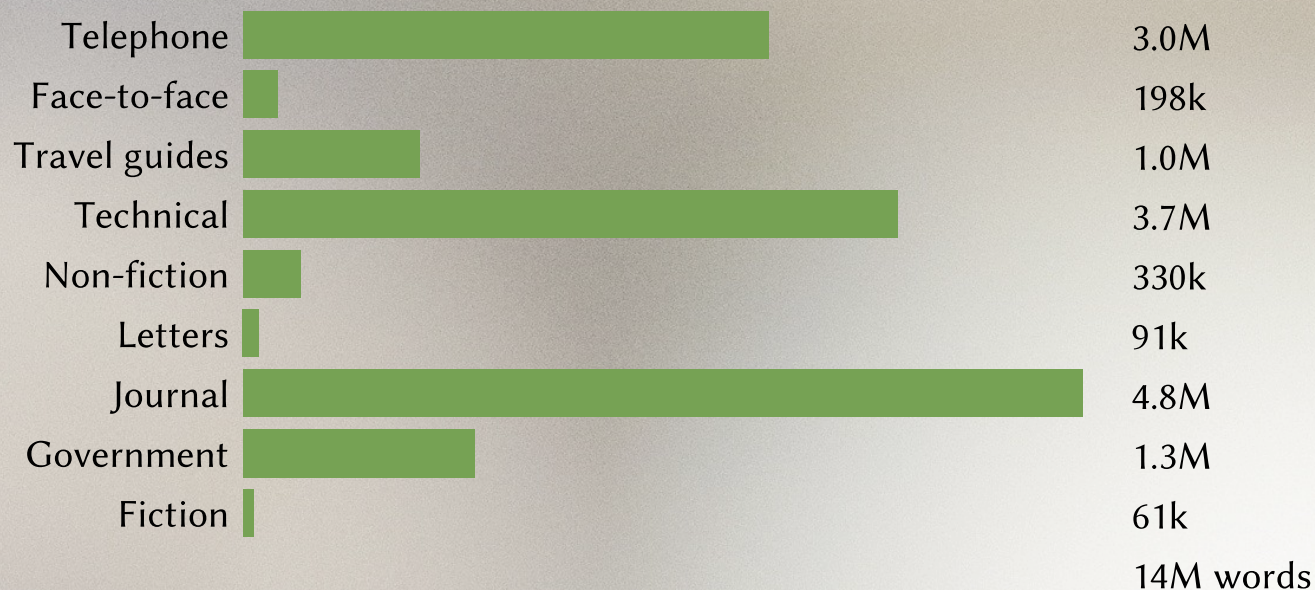
The ETS claims its *e-rater* accounts for prompt-relevance, as well as:

- errors in grammar (e.g., subject-verb agreement)
- usage (e.g., preposition selection)
- mechanics (e.g., capitalization)
- style (e.g., repetitious word use)
- discourse structure (e.g., presence of a thesis statement, main points)
- vocabulary usage (e.g., relative sophistication of vocabulary)
- sentence variety
- source use
- discourse coherence quality

I compiled metrics to stand in for scoring criteria:

Completion	Token count ($r = 0.72$)
Vocabulary	Type count ($r = 0.73$) Mean word length ($r = 0.16$) Word frequency measure ($r = 0.63$)
Narrative	Linking words (<i>however, moreover, nevertheless</i>) per token ($r = 0.02$)
Complexity	Mean sentence length ($r = -0.02$) Number of semicolons ($r = 0.06$) Number of prepositional phrases ($r = 0.25$) Depth of longest branch in dependency tree ($r = 0.37$)

For the frequency measure, I built a frequency list from the American National Corpus (anc.org)...



...and calculated (arbitrarily) the sum
of the rank of each word token:

“Because I could not stop for Death, he kindly stopped for me.” → 9,164

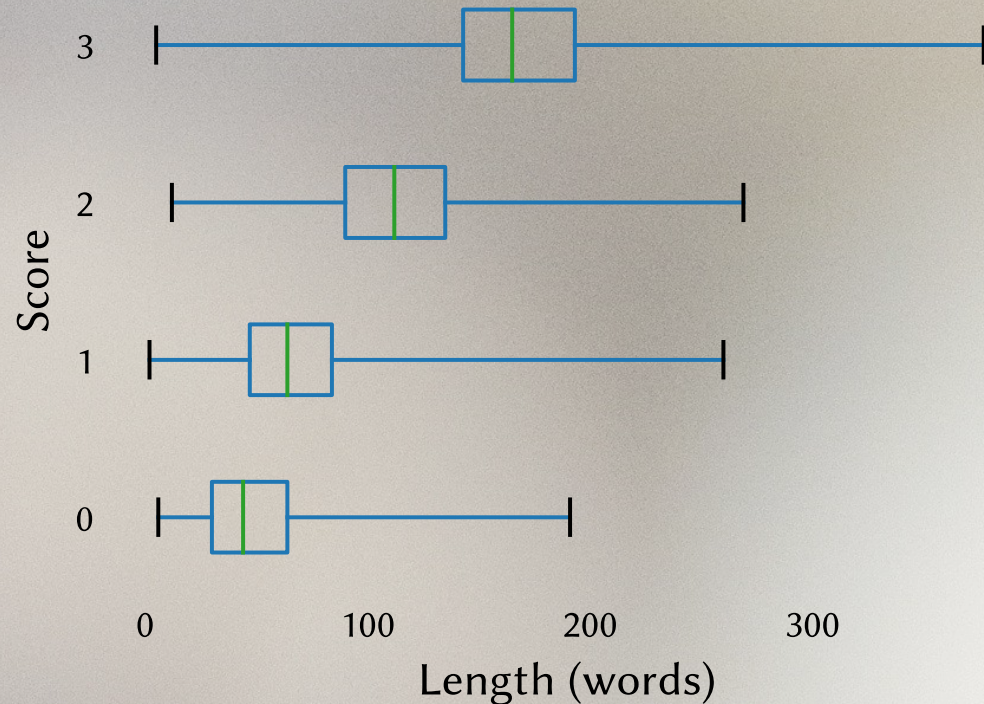
“The boy stood on the burning deck whence all but he had fled.” → 23,815

“I was the shadow of the waxwing slain by the false azure in the windowpane.” → 86,636

“’Twas brillig, and the slithy toves did gyre and gimble in the wabe.” → 146,103

Length is correlated with score ($r = 0.72$)...

82 words corresponds to a 1-point score gain



...but some top-scoring essays are ludicrously short:

The features of the setting affect the cyclist in many ways. It made him tired thirsty and he was near exhaustion.

If it's a good day the cyclist will want to rid. If it is a bad day then they will not want to but probably will.

He is going on a journey on his bike. He has to go down hills and deal with the factt that has has no water. That's basically what the setting is about.

Reserved need to check keenly

Without an objective way of pruning these,
I decided to leave them in the dataset.

k-NN with 4 centroids revealed next to nothing:



Conventional models yielded modest test scores:

Linear regression: **0.57**

LASSO regression: **0.57** $\alpha = 0.01$

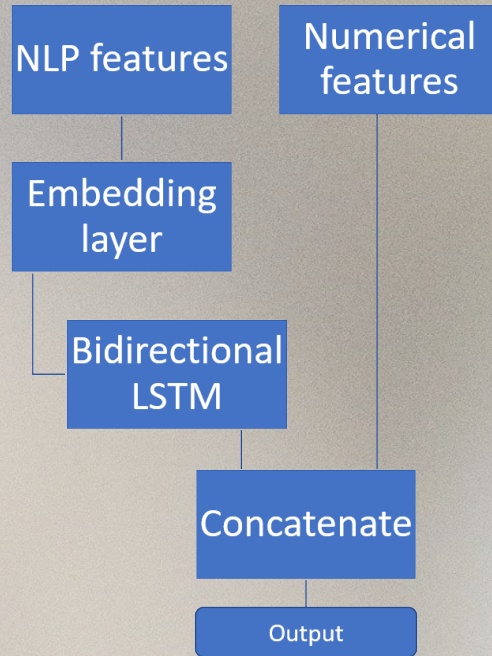
Gaussian naïve Bayes: **0.53**

Support vector machine: **0.64** $\alpha = 1$

AdaBoost: **0.58**

ExtraTrees: **0.64** 1,000 estimators, maximum depth = 300

RNNs can be designed to input both NLP features (document vectors) and metadata:




```
# Define inputs
vector_input = Input(shape=(1000,)) # Word vectors, in series of length 1,000
meta_input = Input(shape=(5,)) # PCA-transformed metadata (types, tokens, etc.)

# Embedding layer turns lists of word indices into dense vectors
rnn = Embedding(
    input_dim = len(vocab),
    output_dim = 96,
    input_length = 1000
)(vector_input)

# GRU layers for RNN
rnn = Bidirectional(GRU(256, return_sequences=True, kernel_regularizer=l2(0.01)))(rnn)
rnn = Bidirectional(GRU(256, return_sequences=False, kernel_regularizer=l2(0.01)))(rnn)

# Incorporate metadata
rnn = Concatenate()([rnn, meta_input])

# Define hidden and output layers
rnn = Dense(128, activation="relu", kernel_regularizer=l2(0.01))(rnn)
rnn = Dense(128, activation="relu", kernel_regularizer=l2(0.01))(rnn)
rnn = Dense(4, activation="softmax")(rnn)

# Define model
model = Model(inputs=[vector_input, meta_input], outputs=[rnn])
```


But it didn't do much better than the others:

Linear regression: **0.57**

LASSO regression: **0.57** $\alpha = 0.01$

Gaussian naïve Bayes: **0.53**

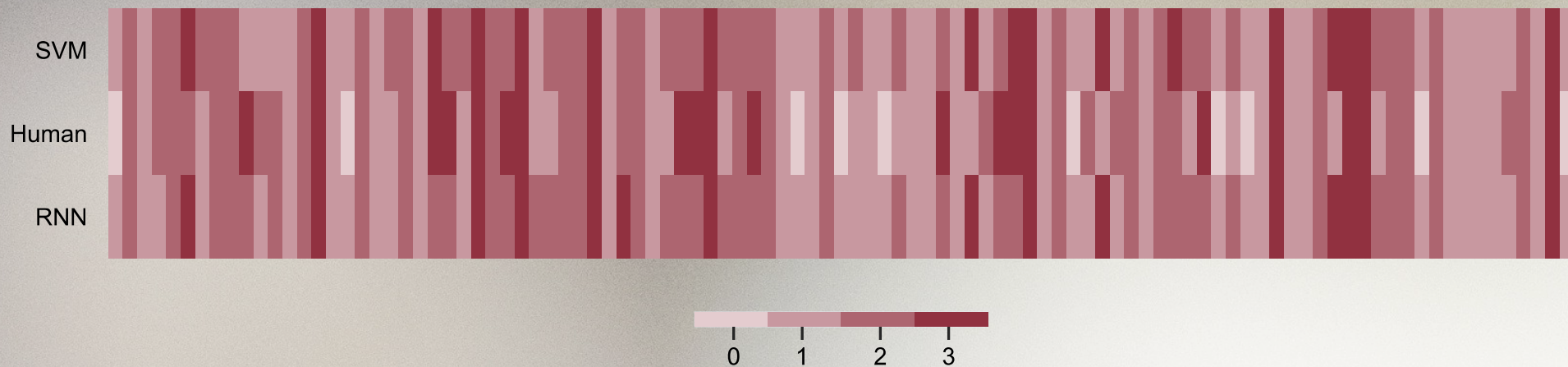
Support vector machine: **0.64** $\alpha = 1$

AdaBoost: **0.58**

ExtraTrees: **0.64** 1,000 estimators, maximum depth = 300

RNN: **0.62**

The SVM and RNN generated similar scores, probably since they were given the same metadata.



Demonstration: EssayScorer.py

```
12 alex pequod:~/C/G/P/C/EssayScorer master$ ./EssayScorer.py
```

```
Type your essay:
```

```
The features of the setting affect the cyclist in many ways. The features of the setting  
that affect the cyclist is the lack of information on where to go and the lack of water.  
This was a problem because he needed water for his trip and directions on where to go.
```

```
Loading NLP data...
```

```
Loading model...
```

```
Preprocessing essay...
```

```
Running model...
```

```
Score: 1
```


Final tally:

- ✓ Completion
- ? Structure
- ✗ Relevance
- ✗ Grammatical correctness

Appendix: Python libraries

```
@show_progress  
def my_fun(i, item):  
    ... do_stuff_to(item) ...
```

```
my_fun(my_list)
```

```
Parsing item 1,969 of 12,976 [=====>
```

```
] 15%, 38:45 remains...
```