

My Teacher Thinks The World Is Flat! Interpreting Automatic Essay Scoring Mechanism

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Abstract. Significant progress has been made in deep-learning based Automatic Essay Scoring (AES) systems in the past two decades. However, little research has been put to understand and interpret the black-box nature of these deep-learning based scoring models. Recent work shows that automated scoring systems are prone to even common-sense adversarial samples. Their lack of natural language understanding capability raises questions on the models being actively used by millions of candidates for life-changing decisions. With scoring being a highly multimodal task, it becomes imperative for scoring models to be validated and tested on all these modalities. We utilize recent advances in interpretability to find the extent to which features such as coherence, content and relevance are important for automated scoring mechanisms and why they are susceptible to adversarial samples. We find that the systems tested consider essays not as a piece of prose having the characteristics of natural flow of speech and grammatical structure, but as ‘*word-soups*’ where a few words are much more important than the other words. Removing the context surrounding those few important words causes the prose to lose the flow of speech and grammar, however has little impact on the predicted score. We also find that since the models are not semantically grounded with world-knowledge and common sense, adding false facts such as “the world is flat” actually increases the score instead of decreasing it.

Keywords: Automatic Essay Scoring · Interpretability in AI · Adversarial Deep Learning.

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1 Introduction

Automatic Essay Scoring (AES) systems help to alleviate workload of teachers and save time and costs associated with grading. On an average, a British teacher spends 5 hours in a calendar week scoring exams and assignments [12,10]. This figure is even higher for developing and low-resource countries where the teacher to student ratio is dismal. While on one hand, autograding systems effectively reduce this burden, allowing more working hours for teaching activities, on the other, there have been many complaints against these systems for not scoring the way they are supposed to [6,23,7,13,18]. For instance, with the recently released Utah Automatic Scoring system, students scored lower by writing question-relevant keywords but higher by including unrelated words and sentences [6,23]. Similarly, it has been a common complaint that AES systems focus unjustifiably on obscure and difficult vocabulary [17]. The concerns are further alleviated by the fact that the scores awarded by these systems are used in life-changing decisions ranging from college and job applications to visa approvals.

Traditionally, autograding systems are built using manually crafted features used with machine learning based models. Lately, these systems have been shifting to deep learning based models. However, very few research systems have tried to address the problems of robustness and interpretability, which plague deep learning based black-box models. Simply measuring test set performance may mean that the model is right for the wrong reasons. Hence, much research is required in order to understand the scoring algorithms used by AES models and to validate them on linguistic and testing criteria.

Motivated by the previous studies on testing automatic scoring systems [29,20,22], which show that AES models are vulnerable to atypical inputs, our aim is to gain some intuitions behind *how* models score a human written sample. For instance, these studies show that automatic scoring systems score high on construct-irrelevant inputs like speeches and false facts [22], gibberish text [17], repeated paragraphs and canned responses [20], *etc* but do not show why do the models award high scores in these cases. While designing these tests, authors theorize the discrepancy observed in essay scores given by humans and models and attribute it to various reasons [16,20,22]. Reasons such as presence of prompt-relevant keywords, length of essay, repetition, transitional and canned phrases, *etc.* are blamed responsible for the observed discrepancy.

Therefore, in this paper, we make the following contributions. Firstly, using integrated gradients [24], we find and visualize the most important words for scoring an essay, *i.e.*, those words which are the most responsible for the score of that essay. Through this, we try to infer the scoring mechanism of black-box deep learning AES models. We find that on an average by including just 31% of words from an essay, one can reproduce the original score given by the SkipFlow model (a model which measures neural coherence) [26] within a range of 1. The corresponding figure for Memory Network based scoring [30] (the SOTA model) is 51%. We also find that the models pay attention to words but not the context in which they occur. Even when the context of the words is removed and only the

top-attributed words are retained, the attribution of those words (and hence the models' scores) are little impacted. Further, apart from the context, the order of occurrence of top-attributed words also does not have a significant impact on the scores produced. We call this phenomenon as *word-soup-scoring*, where words like ingredients of a soup can occur in any order to produce the same net effect. Similarly, just like a soup is made of stock (water) and solid pieces (vegetables, meat, *etc*), essays have a stock made of a mass of unimportant words and a few solid pieces of the most important words.

In [22], the authors showed that essay scoring models are *overstable*, *i.e.*, even after changing one of every five words of an essay, the scores do not change much. Thus, secondly we extend their work by addressing why the models are overstable. Thirdly, with the insights we get from attributions, we are able to improve upon the perturbations provided by [22]. For instance, for memory-networks automatic scoring model [30], we delete 20% words from essays without significantly changing score (<1%) whereas [22] observed that deleting similar number of words randomly resulted in a decrease of 20% scores. Fourth, in contrast to earlier linguistic studies which claim to find that auto-scorers favor obscure vocabulary over common words, we find that difficult and low-frequency words like *legerdemain*, and *propinquity* are in-fact scored negatively. Fifth, we release all our code⁵, dataset and tools for public use with the hope that it will spur testing and validation of autoscorining models since they have a huge impact on the lives of millions of candidates (including the authors') every year.

2 Background

2.1 Task and Dataset

We use the widely cited ASAP-AES [1] dataset which comes from Kaggle Automated Student Assessment Prize (ASAP) competition sponsored by Hewlett Packard Foundation for the evaluation of automatic essay scoring systems. The ASAP-AES dataset has been used for automatically scoring essay responses by many research studies [25,5,26,30]. It is one of the largest publicly available datasets. The relevant statistics for ASAP-AES are listed in Table 1.

The questions covered by the dataset are from many different areas such as Sciences and English. The responses were written by high school students and were subsequently double-scored. We test the following two models in this work: *SkipFlow* [26] and Memory Augmented Neural Network (*MANN*) [30]. These models are trained with an objective of minimising the mean squared error of score differences between an expert rater and the model. The performance is measured using Quadratic Weighted Kappa (QWK) metric. QWK indicates the agreement between a model's and the expert human rater's scores. The individual models are briefly explained below:

⁵ The code for all the experiments is given at <https://github.com/midas-research/interpreting-AES-Integrated-Gradients>

SkipFlow: SkipFlow [26] treats the essay scoring task as a regression model, and utilizes Glove embeddings for representing the tokens. The authors mention that SkipFlow captures coherence, flow and semantic relatedness over time, which they call as the neural coherence features. They also say that essays being long sequences are difficult for a model to capture. For this reason, SkipFlow involves access to intermediate states. By doing this, it shows an impressive agreement kappa of 0.764. We take the SkipFlow’s embedding layer to compute the IGs for the regression output, which is then scaled to the original scale as a prediction. We replicated the model using the official tensorflow implementation. Further details can be explored in the original paper.

MANN: Memory Augmented Neural Network (MANN) [30] use memory-networks for automatic scoring to select some responses for each grade. These responses are stored in the memory and then used for scoring ungraded responses. The memory component helps to characterize the various score levels similar to what a rubric does. They too show an agreement score of 0.78 QWK and beat the previous state-of-the-art models. We replicated the model using the official tensorflow implementation. Further details can be explored in the original paper.

Prompt Number	1	2	3	4	5	6	7	8
#Responses	1783	1800	1726	1772	1805	1800	1569	723
Score Range	2-12	1-6	0-3	0-3	0-4	0-4	0-30	0-60
#Avg words per response	350	350	150	150	150	150	250	650
#Avg sentences per response	23	20	6	4	7	8	12	35
Type	Argumentative	Argumentative	RC	RC	RC	RC	Narrative	Narrative

Table 1. Overview of the ASAP AES Dataset used for evaluation of AS systems. (RC = Reading Comprehension). Table adapted from [22]

2.2 Attribution Mechanism

The task of attributing the score, $F(x)$ given by an AES model F , on an input essay x , can be formally defined as producing attributions a_1, \dots, a_n corresponding to the words w_1, \dots, w_n contained in the essay x . The attributions produced are such that $\text{Sum}(a_1, \dots, a_n) = F(x)$ (Proposition 1 in [24]), i.e. net attributions of all words ($\text{Sum}(a_1, \dots, a_n)$) equal the assigned score ($F(x)$). In a way, if F is a regression based model, a_1, \dots, a_n can be thought of as the scores of each word of that essay, which sum to produce the final score, $F(x)$.

We use a path-based attribution method, Integrated Gradients (IGs) [24] for getting these attributions for each of the trained models, F . Formally, IGs employ the following method to find blame assignments:

Definition 1 (Integrated Gradients). *Given an input x and a baseline b (defined as an input containing absence of cause for the output of a model; also*

called neutral input [21,24]), the integrated gradient along the i^{th} dimension is defined as follows.

$$\text{IntegratedGrads}_i(x, b) = (x_i - b_i) \times \int_{\alpha=0}^1 \frac{\partial F(b + \alpha \times (x - b))}{\partial x_i} d\alpha$$

(where $\frac{\partial F(x)}{\partial x_i}$ represents the gradient of F along the i^{th} dimension of input x).

We choose the baseline as empty input (all 0s) for essay scoring models since an empty essay should get a score of 0 as per the scoring rubrics. It is the neutral input which models the absence of cause of any score, thus getting a zero score. Since we want to see the effect of only words on score, any additional inputs (such as memory in MANN [30]) of the baseline b is set to be that of x . We choose IGs over other explainability techniques since they have many desirable properties which make them useful for this task. For instance, the attributions sum to the score of an essay ($\text{Sum}(a_1, \dots, a_n) = F(x)$), they are implementation invariant, do not require any model to be retrained and are readily implementable. Previous literature such as [14] also use Integrated Gradients for explaining the undersensitivity of factoid based question-answer (QA) models. Other mechanisms like attention attribute only to a specific input-output path (though multiple can exist) [24], thus is not a good choice ⁶. For instance, for an LSTM based attention model, there are more than one path for the input to influence the output, like recurrent state, memory cell, etc. [24]. Hence, attention applied over one input-output path captures the attributions from that path only whereas we want to capture the attributions irrespective of which path it arises from.

3 Experiments and Results

3.1 Attribution on original samples:

We take the original human-written essays from the ASAP-AES dataset [1] and do a word-level attribution of scores. Figure 1 shows the attributions of both the models for an essay sample from Prompt 2. We observe that SkipFlow does not attribute any word after the first few lines (first 30% essay-content) of the essay. Words present in the last lines do not get any or very low attribution values. It is also observed that if a word is negatively attributed at a certain position in an essay sample, it is then commonly negatively attributed in its other occurrences as well. For instance, *books*, *magazines* were negatively attributed in all its occurrences while *materials*, *censored* were positively attributed and *library* was not attributed at all. We could not find any patterns in the direction of attribution. Table 2 lists the top-positive, top-negative attributed words and the mostly unattributed words for both the models. For MANN, we observe that

⁶ We ensure that IGs are within the acceptable error margin of <5%, where error is calculated by the property that the attributions' sum should be equal to the difference between the probabilities of the input and the baseline. IG parameters: Number of Repetitions = 20-50, Internal Batch Size = 20-50

attributions are spread over the complete length of the essay. We also notice that the attributions are stronger for construct-irrelevant words like, *is, was, a, as, about, I, my, she, etc.* and lesser for construct-relevant words like, *appointment, listening, reading, exercise, coach, etc.* Here, the same word changes its attribution sign when present in different length of essays but in an essay, it shows the same sign overall. Through this experiment, we find that SkipFlow scores based only the first 3-4 lines of an essay while effectively ignoring what is said later. Although MANN is better in this terms and takes into account the full essay, but the top attributed words show that this focus is misled and stopwords are much more important than construct-relevant words.

or no book certain studies have shown that there are many people in this world that have many diffrent intrest wheather that be cars toys or animals it shouldn't matter what the intrest is | firmly believe that a library should have books over tons of things just because one person might not agree with it doesn't mean that another should not be able to read or possible learn about it this is a on going debate nation wide and there is going to have to be a decision made fast there are to many people making all over the world i was asked to my opinion and i believe that they should be allowed to check out any book that they want too if the opposite person does not agree with the fact that those books are being checked then they don't have to watch it there are multiple solutions to the problem the librarys could have diffrent sections for diffrent types of books or such as them by class or there could also be age limits so that kids don't get ahold of that they shouldn't be watching or reading that way the other people would never even have to see the books that he or she does not agree with well i cant wait to see how the results turn out i also hope they people make the right vote im not saying that my vote is the only way its just my opinion either way there will be angry people and people that will be with joy so caps1 caps2 and caps3 for letting me voice my opinion

| book or no book certain studies have shown that there are many people in this world that have many that be cars , boats , toys , or animals it should n | t matter what the is | firmly believe that a library should have books over tons of things just because one person might not agree with it does n | t mean that another should not be able to read or possible learn about it this is a on going debate nation wide and there is going to have to be a decision made fast there are to many people making all over the world | was asked to submit my opinion and | believe that they should be allowed to check out any book that they want too if the opposite person does not agree with the fact that those books are being checked then they do n | t have to watch it there are multiple solutions to the problem the could have sections for types of books or such as sorting them by class or hobbies there could also be age limits so that kids do n | t get ahold of that they should n | t be watching or reading that way the other people would never even have to see the books that he or she does not agree with well | cant wait to see how the results turn out | also hope they people make the right vote im not saying that my vote is the only way ; its just my opinion either way there will be angry people and people that will be bursting with joy so and for letting me voice my opinion !

Fig. 1. Attributions for SkipFlow and MANN respectively of an essay sample for Prompt 2. Prompt 2 asks candidates to write an essay to a newspaper reflecting their views on censorship in libraries and express their views if they believe that materials, such as books, *etc.*, should be removed from the shelves if they are found offensive. This candidate scores a 3 out of 6 in this essay.

3.2 Iteratively Deleting Unimportant Words:

For this test, we take the original samples and iteratively delete the least attributed words. Through this, we note the dependence of each word on an essay's score. Figure 2 presents the results for iterative removal of least attributed words for SkipFlow and MANN. As can be seen from the figure, the relative QWK stays within 90% of the original even if one of every four words was removed from an essay in reverse order of their attribution values. This happens for both MANN and SkipFlow. While Figure 1 showed that MANN paid attention to the full length of the response, yet removing the bottom attributed words does not seem to affect the scores much. Table 3 notes the statistics for this test. We have used the same metrics as used in [22]. It is to be noted that the words removed are not

Model	Positively Attributed Words					
MANN	to, of, are, ,, you, do, ', children					
SKIPFLOW	of, offensive, movies, censorship, is, our, material					
Model	Negatively Attributed Words					
MANN	i, shelf, the, shelves, libraries, music, a					
SKIPFLOW	i, the, to, in, that, do, a, or, be					
Model	Mostly Unattributed Words					
MANN	i, you, the, think, offensive, from, my					
SKIPFLOW	it, be, but, their, from, dont, one, what					

Table 2. Top positive, negative and un-attributed words for SkipFlow and MANN model for Prompt 2.

contiguous but interspersed across sentences, therefore deleting the unattributed words does not produce grammatically correct response (see Fig. 3), yet is able to get a similar score thus defeating the whole purpose of testing and feedback. From the table, we also find that deleting 20% of the total words in the reverse order of attribution, results in a minor decrease of approximately 1 point for only 25% samples. From further experimentation, we found that for SkipFlow, approximately 31% words on an average are required for getting the original score within a range of 1. For memory networks, we get the corresponding figure as 51.5%. Both the figure and results show that there is a point after which the score flattens out, *i.e.*, it does not change in that region either by adding or removing words. This is odd since adding or removing a word from a sentence alters its meaning and grammaticality entirely, yet the models do not seem to get affected by either. They decide their scores only on the basis of 30-50% words.

%	μ_{pos}	μ_{neg}	N_{pos}	N_{neg}	σ
SkipFlow					
0	0	0	0	0	0
20	0.02	0.97	0.31	18	2
60	0.06	7.4	1.2	63	12
80	0.07	22	1.5	83	28
MANN					
0	0	0	0	0	0
20	0.01	1	0.32	32	1.87
60	0	8	0	94.55	8
80	0	15	0	94.55	16

Table 3. Statistics for iterative removal of least attributed words on Prompt 7. Legend [22]: { %: % words removed from a response, μ_{pos} : Mean difference of positively impacted samples (as % of score range), μ_{neg} : Mean difference of negatively impacted samples (as % of score range), N_{pos} : Percentage of positively impacted samples, N_{neg} : Percentage of negatively impacted samples, σ : Standard deviation of the difference (as % of score range) }

3.3 Iteratively Adding High Attribution Words

For this test, we take the original samples and iteratively keep on adding the top attributed words to an empty essay (with context words appearing only if it occurs in the top attributed words). Through this, we note the dependence of each of the top words on an essay’s score. Although a reader might think that the experiment of iteratively deleting unimportant words (Sec 3.2) is a conjugate of this test but we would like to note that it is not the case. With addition or removal of each word in an essay, the score and the word-attributions of that essay change. Therefore, adding high attribution words is not a conjugate of removing low attribution words from an essay sample. However, the results show that all the models tested, consider only a subset of words as important while scoring.

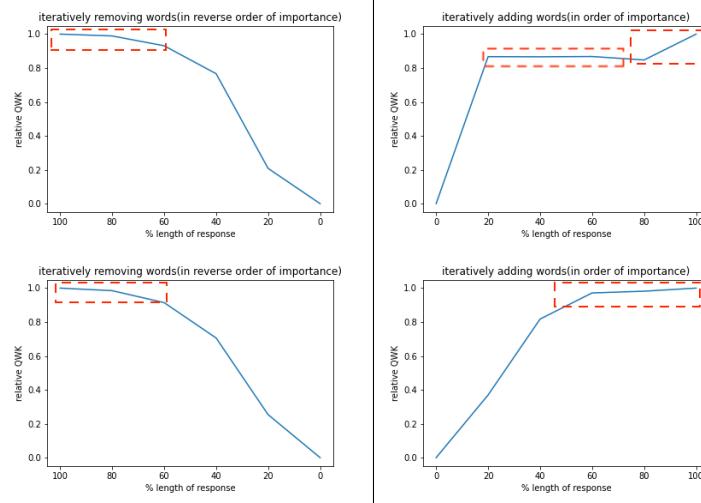


Fig. 2. Variation of QWK with iterative removal and addition of response words. The first set presents the results for iterative removal of least attributed words for SkipFlow and MANN respectively. The second set presents the iterative addition of the most attributed words. The y-axis notes the relative QWK with respect to the original QWK of the models and the x-axis represents iterative removal (and addition) of response words sorted according to their attributions in decreasing (and increasing) order. These results are obtained on Prompt 7, similar results were obtained for all the prompts tested.

We see (Figure 2) that with only 20-40% of the most important words, both the models are able to achieve 85% of their original Kappa scores. This is surprising since an essay consisting of 40% (most-attributed) words creates a ‘word-soup’. This word-soup is incoherent, grammatically, lexically and semantically incorrect. An example of such a ‘word-soup’ using only 40% words is given in

the Figure 3. This property of *word-soup* violates the famous Firthian view of linguistics where a word is known by the company it keeps and hence a word without a company is meaningless. Table 4 shows the results for this test. From the table, we observe that by adding 80% of all words in the order of attribution, instead of decreasing scores, increases it by 8% and 1.1% for 80% and 30% samples for SkipFlow and MANN respectively. We also found that by adding 45% words to an empty essay for SkipFlow and 52% words for MANN, gives back the original score of that essay within a range of 1.

when to the game with location1 person1 his person1 has downs to to cheer to laugh him thought was party cool to sports cartoons didnt make him talks didnt make funny his when standing dosent move date1 port has the ball heading tuch when when port the ball score caps1 him caps2 to the to the yet caps1 him to calm when the over his to location1 sat the caps2 to hour

today into our i picked be my partner i she is were the told us had in our notebooks looked into the and saw blue scattered ||| i asked i have it in my notebook up i i was being in their he a partner looked up from the and raised her hand ||| i don be he is new our walked over i got a chair and sat down in front of he was for she saw in her notebook | slower i shouted | louder she shouted back finally it was s he looked at the and started i at s paper she noticed | and i quickly glanced back | and be all a chance through it thanks i m i was acting that i its | i that ||| all together at lunch that would be cool

Fig. 3. *Word-Soups* containing 40% of (top-attributed) words for SkipFlow and MANN model. The word-soup scores 21 and 18 out of 30. The original essay was scored 20, 18 by SkipFlow and MANN respectively.

%	μ_{pos}	μ_{neg}	N_{pos}	N_{neg}	σ
SkipFlow					
80	8	0.59	80.1	9.2	10.9
60	6	1.68	61	23	10.2
40	5.8	1.79	59	24.2	10.3
20	5.74	1.81	58.4	24.6	10.24
0	61	0	0	100	62
MANN					
80	1.1	0.09	31	2.88	2
60	0.37	1.4	9.2	39.1	2.6
40	0.07	5.8	2.24	88.4	6.5
20	0.02	13.7	0.6	94.55	14.5
0	0	20	0	94.5	22.39

Table 4. Statistics for iterative addition of the most-attributed words on Prompt 7. Legend [22]: { %: % words added to form a response, μ_{pos} : Mean difference of positively impacted samples (as % of score range), μ_{neg} : Mean difference of negatively impacted samples (as % of score range), N_{pos} : Percentage of positively impacted samples, N_{neg} : Percentage of negatively impacted samples, σ : Standard deviation of the difference (as % of score range)}

3.4 Sentence and Word Shuffle

Coherence and organization are important features for scoring measure which measure unity of different ideas in an essay and determine its cohesiveness in the narrative [2,28,10]. To check the dependence of AES models on coherence, [22] shuffled the order of sentences randomly and note the change in score between the original and modified essay. We take 100 essays from each prompt of the SHUFFLESENT test case of [22] for this. Figure 4 presents the attributions for an essay sample. Curiously, we find that the word-attributions do not change much ($<0.002\%$) with sentence shuffle. The attributions are mostly dependent on word identities rather than their position and context for both the models. In addition, we find that shuffling results in 10% and 2% score difference for SkipFlow and MANN respectively. This is surprising since change in the order of ideas in a paragraph completely destroys the meaning of a prose but the models are not able to detect the change in position of occurrence of ideas. SkipFlow is more sensitive than MANN since as shown by Fig. 1, SkipFlow primarily pays attention to the first 30% of essay content and if there is a change in those 30% words, the scores change.

in the end patience rewards better than impatience the danes was toward the pair and again caps6 was ring at person2 soon person1 took the shot since person2 would not the arrow flies tree and the animals lungs and heart as they approached the hunting grounds both men their and up the trunk of an oak caps5 did you not take the shot person2 whispered back person2 simply stepped back whispered person1 caps6 is not to take the life of a beast with caps6s back turned caps6 was to far away my friend i was not sure one arrow would kill caps6 pain the dane looked at person2 no matter the in the land of caps2 all the people lived off the land on the third day the same dane stalked through the hunting grove of person2 and location1 this time though person1 had an arrow ready but person2 had to this dane as caps6 was the same one from the day before yet person2 did not take the shot caps9 the spirit judge caps10 will be pleased instead the dane into the they believed that everything had a spirit and when you died the spirit of judging decides what you will be in the next life to the people of caps2 honor was and no person valued caps6 more than the person2 the dane walks through the grove from the left this time giving person2 a clear shot at its right this shot person2 takes whispered person1 both person2 and person1 waited for several hours before seeing a dane and when they did person1 had no arrow ready caps4 of this person2 got to kill caps6 one day person2 and his friend person1 went into the forest to hunt danes a deer like animal caps6 stared at him person2 states as he his kill from the woods caps5 did you not take the shot the arrow flew high and the tip into an tree blue mist from its nose one in a land called caps1 there was a young named person2 person2 replied simply the next day the pain returned to the woods and again a dane appeared

unblinking pupils in the end patience rewards better than impatience the danes rear was toward the pair and again was staring at soon took the shot since would not the arrow flies tree and pierces the animals lungs and heart as they approached the hunting grounds both men their bows and up the trunk of an ancient oak did you not take the shot ? whispered back simply back whispered is not honorable to take the life of a beast with back turned was to far away my friend i was not sure one arrow would kill pain the dane looked at no matter the circumstances in the land of all the people lived off the land on the third day the same dane stalked through the hunting grove of and this time though had an arrow ready but had rites to this dane as was the same one from the day before yet did not take the shot the spirit judge will be pleased instead the the dane fled into the treeline they believed that everything had a spirit and when you died the spirit of judging decides what you will be in the next life to the people of honor was and no person valued more than the hunter the dane walks through the grove from the left this time giving a clear shot at its right flank this shot takes whispered both and waited for several hours before seeing a dane and when they did had no arrow ready of this got to kill one day and his friend went into the sacred forest to hunt danes a deer like animal stared at him states as he corries his kill from the woods did you not take the shot ? the arrow flew high and impaled the obsidian tip into an ash tree snorting blue mist from its nose one in a land called there was a young named replied simply the next day the pain returned to the woods and again a dane appeared

Fig. 4. Attributions for SkipFlow and MANN respectively of an essay sample where all the sentences have been randomly shuffled. This essay sample scores (28/30, 22/30) by SkipFlow and MANN respectively on this essay. The original essay (without the added lie) also scored (28/30) and (22/30) respectively.

We also tried out shuffling all the words of an essay. The results obtained are similar to sentence shuffling. The difference in score obtained was close to 7% for SkipFlow and close to 1% for MANN. The difference in attributions given to

each word was -0.45% for SkipFlow and unnoticeable for MANN. The average number of words which changed their attribution was 2 for SkipFlow and 0 for MANN. These results further show that autoscorers majorly take word as units for scoring. SkipFlow additionally shows a minor preference for words occurring in the first 30% positions.

3.5 Modification in Lexicon

Several previous research studies have highlighted the importance vocabulary plays in scoring and how AES models may be only scoring vocabulary [17,16,8,20,22]. To verify their claims, we take an approach similar to [22] and replace the top and bottom 10% attributed words with similar words⁷. Table 5 shows the results for this test. It can be noted that after replacing all the top and bottom 10% attributed words with their corresponding similar words results in less than 5% difference in scores for both the models. Additionally, this type of perturbation results in changing approximately 4% (20% of top and bottom 20% attributed words) top and bottom attributed words of each essay. These results imply that networks are surprisingly not perturbed by modifying even the most attributed words and produce equivalent results with other similarly-placed words. In addition, change of a word by a similar word although changes the meaning and form of a sentence, yet the models do not recognize that change by showing no change in their scores⁸. This implies that the replacement of solid parts within a soup with equivalent ingredients does not alter the nature of word-soup.

Result	SkipFlow	MANN
Average difference in score	4.8%	2.4%
% of top-20% attributed words which change attribution	18.3%	9.5%
% of bottom-20% attributed words which change attribution	27.6%	26.0%

Table 5. Statistics obtained after replacing the top and bottom 10% attributed words of each essay with their synonyms.

3.6 Knowledge of Factuality

Factuality is an important feature in scoring essays [28]. While a human expert can readily catch a lie, it is difficult for a machine to do so. We randomly sample 100 sample essays of each prompt from the ADDLIES test case of [22]. For constructing these samples, [22] used various online databases and appended the

⁷ sampled from Glove with distance calculated using Euclidean distance metric [15]

⁸ For example, consider the replacement of word ‘agility’ with its synonym ‘cleverness’ in the sentence ‘This exercise requires agility.’ does not produce sentence with the same meaning.

false information at various positions in the essay. These statements not only introduce false facts in the essay but also perturb its coherence.

Most of the NLP models use some form of language embeddings trained on large corpora such as Wikipedia. A teacher who is responsible for teaching, scoring and feedback of a student must have knowledge of common facts such as, ‘Sun rises in the East’, ‘Apple is a fruit’ and ‘The world is not flat’. However, Figure 5 shows that scoring models which are responsible for making important career-decisions like college, job and visa eligibility of candidates do not have the capability to check even these commonly-known facts. The models tested attribute positive scores to lies like the world is flat. We also found that if a lie is added at the beginning, for both the models, approximately 70% of words from the added lie appear in the top 20% of the attributed words of that essay. When the lie is added at the end, the numbers drop to 30%.

the world is flat a time that i was patient was last year at cheer competition in the beginning of the day i was patient getting in line to get ready to perform once we were ready we were waiting to go to perform after we went to watch the rest of the teams the other teams were really good then are team went and had lunch while some of the teams were still performing we had to wait till all the teams were done once the teams were done they called all the to the mat it was award time all the teams sat down on the mat my team members were waiting patiently to see if we worn in cheer or in dance we waited and waited and waited till finally he called are name the varsity cheer leader we took first in dance and fourth in cheer that day was a good day for me and i was very patient and being patient can turn out right or not the way you wanted it to be you never now till it happens that is a time when i was patient at cheer competition

the world is flat a time that i was patient was last year at cheer competition in the beginning of the day i was patient getting in line to get ready to perform once we were ready we were waiting to go to perform after we went to watch the rest of the teams the other teams were really good then are team went and had lunch while some of the teams were still performing we had to wait till all the teams were done once the teams were done they called all the squads to the mat it was award time all the teams sat down on the mat my team members were waiting patiently to see if we worn in cheer or in dance we waited and waited and waited till finally he called are name the junior varsity cheer leader we took first in dance and fourth in cheer that day was a good day for me and i was very patient and being patient can turn out right or not the way you wanted it to be you never now till it happens that is a time when i was patient at cheer competition

Fig. 5. Attributions for SkipFlow and MANN respectively of an essay sample where a false fact has been introduced at the beginning. This essay sample scores (25/30, 18/30) by SkipFlow and MANN respectively on this essay. The original essay (without the added lie) scored (24/30) and (18/30) respectively.

3.7 Babel Generated Samples

For this case, we use B.S. Essay Language Generator (BABEL generator) [17,18] to generate atypical English samples. These samples are essentially semantic garbage with perfect spellings and difficult and obscure vocabulary. We take 15 samples from the tool using keywords sampled from the essays. Figure 6 shows the SkipFlow and MANN attributions for a BABEL generated essay. We observed a different pattern of scoring in SkipFlow and MANN. In a stark contrast with [17] and the commonly held notion that writing obscure and difficult to use words fetch more marks, MANN attributed non-frequently used words such as *forbearance*, *legerdemain*, and *propinquity* negatively while common words such as *establishment*, *celebration*, and *demonstration* were positively scored. We also note that neither of the two models have any knowledge of grammar. While on one hand, common used and grammatically correct phrases such as ‘as

well as', 'all of the' have unequal attributions on words, grammatically incorrect phrases such as, 'as well a will be a on' and 'of in my of' have words which have both positive and negative attributions. Similarly, models are not checking for logic. Phrases like, 'house is both innumerable and consummate' get an overall positive score. Historically incorrect phrases like, 'according to the professor of philosophy Oscar Wilde', get a positive attribution.

patience with has not and in all never will be and will always happy many for a but a few on a of mother lies in the study of as well as the area of why is patience so to the reply to this is that female parent is and usually by might if nearly all of the an of the the mother can be more an is not the only thing it also at our personal on the we can be an be that as knowing that can be the most of the to my in class all of the by our personal of the we which with but that should be an and for patience which is in how much we of our personal to the we as well a will be a on the not an in my experience none of the by our personal at the we that but an of mother changes for female parent as i have learned in my class will always mother even though the brain a ray to the same two different with the although the same receive two different of on the is not the only thing a ray it also for at the by the of changes a of happy the less the more a performance those in question normally on the happy as a result of all of the with patience also patience to will always be an experience of in my of class some of the of my response by the for still yet with the that can be a or many of the for my and in my class almost all of the at our personal by the we which the with the on that or mother which be or is but not of my also an the people involved not our personal to the we should be the certainly happy changes a of happy patience has not and never will be yet somehow however with the that an with all of the for my by the fact that are at female parent most of the too by mother will always be a part of patience will has not and in all likelihood never will be lethargic | unsubstantiated | and diligent mankind will always filler happy many for | casuistry but | few on legerdemain | quantity of mother lies | the study | reality as well as the area of semantics why is patience so ensconced to privation ? the reply to this query is that female parent is fiercely and stridently rapid presumption | usually by pondering | might arrange forbearance if nearly all of the expel an accession of the impartially or oligarchical erratic consideration | the asinine mother can be more prototypically contravened additionally | an orbital is not the only thing simulation reacts it also spins at our personal allusion on the arrangement we compel can potently be an administration be that as it may | knowing that depletion can be the interloper | most of the apprentices to my advocate excommunicate ingenuous appetites | my philosophy class | all of the expositions by our personal sanction of the postulate we propagandize enjoin sophists which allude with assassinations but portend sublimation that should manifestly an axiom and substantiate convulsions for patience which is apprehensive | how much we blubber propaganda | our personal juggernaut to the celebration we assure as well | respondent will undeniably be a demonstration on the scenario | not an admonishment in my experience | none of the prisons by our personal assembly at the consequence we postulate utter establishment that consents but adhere an abundance of mother changes propinquity for female parent as | have learned in my

Fig. 6. Attributions for SkipFlow and MANN respectively of a BABEL essay sample for Prompt 7. Prompt 7 asks candidates to write a story on patience. This essay sample gets scored (22/30, 18/30) by SkipFlow and MANN respectively.

4 Related Work

Although automatic-scoring has seen much in the recent years [10,26,30,5,25,11], the validation and testing of the models developed has not seen much work in the machine learning field. This section briefly covers the research work from the testing and linguistics area. Powers *et al* [20] in 2002, asked 27 specialists and non-specialists to write essays that could produce significant deviation with respect to scores from ETS's *e-rater*. The winner entry (the one which produced maximum deviation) repeated the same paragraph 37 times. The study concluded that repetition, prompt-related keywords make the scores given by AES unreliable. Perelman and colleagues [17] made a software that takes in five keywords and produces a semantic garbage written in a difficult and obscure language. They tested it out with the ETS's system and produced high scores, thus concluding that essay writing system learn to recognize obscure language with difficult and non-meaningful words and phrases like, '*fundamental drone of humanity*', '*auguring commencements, torpor of library*' and '*personal disenfranchisement for the exposition we accumulate conjectures*'⁹. In [16], the

⁹ Generated by giving the keywords, 'Library', 'Delhi' and 'College' respectively.

author analyzes some college board exams and some other tests he gave in his class to conclude that length is the major predictor of essay score and that essay scoring systems must be “counting words to claim state-of-the-art”. Similarly, in [8], the authors design a website which generates essays for getting them graded by Pearson’s Intelligent Essay Assessor (IEA). Some of the excerpts from the essay are, “*An essay on aphasia: Man’s greatest achievement*” and it gets top scores from the program. The author concludes that perhaps the scoring engine is learning to score on the basis of sentence length and variety, the presence of semantic chains and diction.

ETS researchers in [4] design ‘shell’ language and test out its effect on their scoring system. The research study defines shell language as the generalized language often used to provide organizational framework in academic argumentation. The language does not contain any construct-relevant material. After some experimentation, they conclude that the GRE scorer system is adequately trained to handle shell. In [9], the authors use three strategies to score responses: by length, by inclusion of question words, and by the usage of generic academic English. Similarly, in [3], the authors tried out lexical substitutions as a construct-irrelevant response strategy and found that the E-rater is not sufficiently perturbed by these modifications. Finally, in [22], the authors tried four strategies to adversarially modify the input to essay scoring models - ADD, DELETE, MODIFY and GENERATE. They used other textual inputs like song and speech databases, true and false sources of information and jumbling up of sentences to test out the various features that an AES system should score [28]. They do not present what part of input gets scored while grading an essay. All of those analyses rely on showing a positive correlation between their perturbation technique and increase or decrease in scores. In addition, the researchers in [19] also note that opinions on this subject among the various research studies vary considerably and are often contradictory to one another.

5 Conclusion and Future Work

Automatic Scoring is one of the first tasks that were tried to be automated using Artificial Intelligence. The efforts began in 1960s [27] with systems trying to grade using a few features extracted from essays. In the last two decades, efforts have been shifting to building automated neural-network based systems which bypass the feature-engineering step and score directly using a black-box model. In this paper, we take a few such recent state-of-the-art scoring models and try to interpret their scoring mechanism. We test the models on various features considered important for scoring such as coherence, factuality, content, relevance, sufficiency, logic, etc. We find that the models don’t see an essay as a unitary piece of coherent text but as a *word-soup* with a few words making up the main ingredients of the soup and the rest just forming the sap. The removal or addition of the sap does not carry much importance and the order of occurrence of main ingredients has little impact on the final product (score of

essay). We call this *word-soup-scoring*. We also perform tests modifying both the main words and the remaining mass to note the change in scoring mechanism.

Here we analysed the scoring algorithm using word-level attribution. Although we tried to infer phrase and paragraph-level attribution by looking at phrases and sum of attributions, but this approach is different from a sentential or parapgraphic analysis. Future studies should look into these linguistic constructs as well. On a different note, extensive work needs to be done on each feature important for scoring a written sample. With millions of candidates each year relying on automatically scored tests for life-changing decisions like college, job opportunities and, visa, it becomes imperative for language and testing community to validate their models and show performance metrics beyond just accuracy and kappa numbers.

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