Automated Essay Scoring: A Survey of the State of the Art

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Automated Essay Scoring
High-stakes Testing, e.g. TOEFL, GRE

Classroom Setting, e.g. homework assignment, in-class writing
Scoring

Holistic Scoring or Dimension-specific scoring

How persuasive is the argument? (Persuasiveness)

How does it adhere to the topic? (Adherence)

How is its logical organization? (Coherence)

How clear is its thesis? (Thesis Clarity)

Some useful feedback to student from teacher

This semester I took History. It has always been one of my favorite classes. History makes me feel knowledgeable, like I’m the only one who understands the world around me, and under. It taught me that there are so many wars in the Middle East, why there is still mistrust between Russia and the United States, but I never thought it would teach me to keep an open mind.

Before I started the course, I firmly believed that all Americans were ignorant and self-absorbed. To me, they take too much pride in their country’s success and not enough in other countries. It seems as though they took too much credit in defeating Germany in World War One when until 1917, Canada did in their country. For that song also seem to prove their knowledge. Jay Leno or this

Are you crazy?

SEE ME
Essay scoring is a time-consuming, laborious task.

For teachers:
- Long hours

For standardized testing services (e.g. ETS):
- High cost, due to amount of human labor required.

For students:
- Inability to judge their own work.
Goals

Provide an overview of the major milestones in AES research since its inception more than 50 years ago

While server books and articles exist, we don’t aware of any useful survey on AES that were published in the past three years
Plan for the talk

- Corpora
- Systems
- Evaluation and State of the Art
- Concluding Remarks
Corpora

5 publicly available English Corpora

- CLC-FCE
- ASAP
- TOEFL11
- ICLE
- AAE

Dimension-Specific
- Organization
- Thesis Clarity
- Prompt Adherence
- Persuasiveness

Holistic
- Persuasiveness
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Holistic Scoring

- Vast Majority of existing AES systems were developed for holistic scoring
  - Corpora manually annotated with holistic scoring are publicly available
  - Holistic scoring technologies are commercially valuable
Holistic Scoring is far from adequate for use in classroom settings

- Merely returning a low holistic score to a student provides essentially no feedback to her on which aspects of the essay contributed to the low score and how it can be improved
Tasks

Holistic Scoring

Dimension-specific Scoring

- They are both challenging
  - Discourse-level problems that involve the computational modeling of different facets of text structure
  - An understanding of essay content is required
Approaches: Off-the-shelf

- As an regression task
  - Linear Regression
  - Support Vector Regression
  - Sequential Minimal Optimization

- As a classification task
  - Logistic Regression
  - Sequential Minimal Optimization
  - Bayesian network classification

- As a ranking task
  - SVM ranking
  - LambdaMART
Approaches: Neural Approaches

- Many recent AES systems are neural-based
  - Many traditional work on AES has focused on feature engineering
  - An often-cited advantage of neural approaches is that they obviate the need for feature engineering
Approaches: Neural Approaches

- Taghipour and Ng, 2016
Approaches: Neural Approaches

- Weakness
  - Some words have little power in discriminating between good and bad essays.
  - Failure to distinguish these under-informative words from their informative counterparts may hurt AES performance.
Approaches: Neural Approaches

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- Solution (Alikaniotis et al., 2016)
  - Train a task-specific word embeddings by augmenting the CW model.
  - These score-specific word embeddings (SSWEs), are then used as features for training a neural AES model.
Approaches: Neural Approaches

- Weakness
  - Aforementioned approaches model a document as a linear sequence of words
  - But in reality, document is in hierarchical structure
Approaches: Neural Approaches

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  - But in reality, document is in hierarchical structure

- Solution (Dong and Zhang, 2016)
  - Model the hierarchical structure by using two convolution layers that correspond to the two level hierarchical structure (i.e. sentence level and word-level)
Approaches: Neural Approaches

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  - Some characters, words and sentences in an essay are more important than the others as far as scoring is concerned.
  - And therefore should be given more attention.
Approaches: Neural Approaches

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- **Solution (Dong et al., 2017)**
  - Incorporate an attention mechanism into the neural network by using attention pooling rather than simple pooling
Approaches: Modeling Coherence

- Motivation (Tay et al., 2018)
  - Coherence is an important dimension of essay quality
  - Holistic scoring can also be improved by computing and exploiting the coherence score of an essay
Motivation

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- Holistic scoring can also be improved by computing and exploiting the coherence score of an essay
Approaches: Transfer Learning

Motivation (Phai et al., 2015; Cummins et al., 2016; Jin et al., 2018)

- Ideally, we can train prompt-specific AES systems
- In practice however, it is rarely the case that enough essays for the target prompt are available for training.
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  - In practice however, it is rarely the case that enough essays for the target prompt are available for training.
  - As a result, many AES systems are trained in a **prompt-independent** manner, meaning that a **small number of target-prompt essays** and a **comparatively larger set of non-target-prompt essays**
  - In that case, the potential **mismatch** in the vocabulary used in the essays written for the source prompt and those for the target prompt may hurt the performance of prompt-independent systems
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Features

- A large amount of work on AES has involved feature development
  - The amount of training data is limited (which is important for neural models to be effective)
  - Neural model may further improved by incorporating hand-crafted features obtained via feature engineering
  - Feature-based approaches and neural approaches should be viewed as complementary rather than competing approached
Features: Length-based

- Length within certain range is found to be highly positively correlated with the holistic score of an essay

- Commonly used features
  - Number of Sentences
  - Number of Words
  - Number of Characters
Features: Lexical

- Divided into two categories
  - Word unigrams, bigrams and trigrams that appear in an essay.
  - Statics computed based on word n-grams, particularly bi-gram

- These word n-grams are useful because they encode the grammatical, semantic, and discourse information about an essay that could be useful for AES
  - the bigram "people is" suggests ungrammaticality
  - the use of discourse connectives (e.g., "moreover", "however") suggest cohesion
Features: Embeddings

- Embeddings can be seen as a variant of n-ram features, are arguably a better representation of the semantics of a word/phrase than word n-grams.

- Three types of Embedding features:
  - Features computed based on embeddings \textit{pertained} on a large corpus such as GLoVE
  - AES-\textit{specific} embeddings
  - \textit{Originally} one-hot word vectors, but are being updated as the neural model that uses these feature is trained.
Features: Word category

- Computed based on wordlist or dictionaries, each of which contains words that belong to a particular lexical, syntactic, or semantic category
  - For instance, features are computed based on lists containing discourse connectives, correctly spelled words, sentiment words

- The presence of certain categories of words in an essay could reveal a writer’s ability to organize her ideas, compose a cohesive and coherent response to the prompt, and master standard English
Features: Prompt-relevant

- Encode the relevance of the essay to the prompt it was written for
  - Intuitively, an essay that is not adherent to the prompt cannot receive a high score

- Common measures of similarity
  - Number of word overlap
  - Word topicality
  - Semantic similarity as measured by random indexing
Features: Readability

- Encode how difficult an essay is to read
  - While good essays should not be overly difficult to read, they should not be too essay to read either

- Common measures of readability in AES
  - Flesch-kindcaid Reading Ease
  - Type-token ration
Features: Syntactic

- Encode the syntactic information about an essay

- Three main types of syntactic features
  - Part-of-speech
  - Parse Tree
  - Grammatical error rates
Features: Argumentation

- Computed based on the argumentative structure
  - Only applicable to persuasive essay
  - Have often been used to predict the persuasiveness of an argument made in an essay

- Argumentative structure
  - Major claim
  - Claim
  - Premise

- Computed based on the argument component and relations
Features: Semantic

- Encode the lexical semantic relations between different words in an essay
- Two main types of semantic features
  - Histogram-based features
  - Frame-based features
- Computed based on the argument component and relations
Features: Discourse

- Encode the discourse structure of an essay
- This feature have been derived from
  - Entity grid
  - Rhetorical structure theory (RST) trees
  - Lexical Chain
  - Discourse function labels
Plan for the talk

• Corpora

• Systems

• Evaluation and State of the Art

• Concluding Remarks
Evaluation and State of the Art

Metrics

- Quadratic Weighted Kappa (QWK)
- Mean Absolute Error (MAE)
- Pearson’s Correlation Coefficient (PCC)
Evaluation and State of the Art

- Holistic Scoring
  - Both QWK and PCC are quite high (on CLC-FCE, ASAP and TOEFL11)

- Dimension-specific Scoring
  - Worse than their holistic counterparts in terms of PCC (on ICLE and AAE)
Evaluation and State of the Art

Nevertheless, these results do not necessarily suggest that holistic scoring is easier than domain-specific scoring

- They are not directly comparable as they are obtained on different corpora
- The number of essays used to train the holistic scoring tends to be larger than those used to train the dimension-specific scores.
- What these results do suggest, however, is that dimension-specific is far from being solved.
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Concluding Remarks

- **Data annotation**
- **AES interactions with other areas**
- **Feedback to students**
- **Explore methods for learning robust models in the absence of large amounts for annotated training data**
- **User studies**