Cognitive Learning: How to Become William Shakespeare

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ABSTRACT

Writing is a fundamental task in our daily life. Existing writing improvement tools mostly focus on low-level grammar error correction, rather than enhancing users' writing styles at the cognitive level. In this work, we present a computational approach that allows learners to have fast but effective learning experience with the help of automatic style transfer, visual stylometry analytics, machine teaching and practice. Our system provides a perfect fusion of vividly visualized style features and principles along with informative examples, which together can shape and drive personalized cognitive

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KEYWORDS
Cognitive Computing; Computational Linguistics; Visual Analytics; Machine Teaching

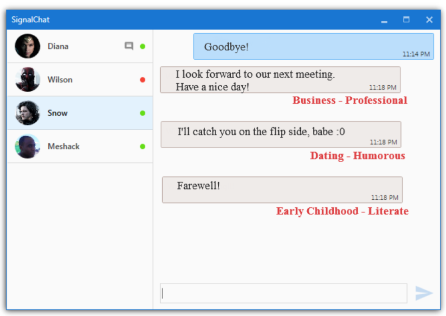

Figure 1: An example of catching different writing styles.

learning experience. We demonstrate the effectiveness of our system in a scenario of learning from William Shakespeare.

INTRODUCTION

Writing is a fundamental task in our everyday life as communications are transmitted more through writing than any other type of media. Many writing improvement tools are available on the market. For example, Grammarly has recently raised $110 million for a better spell check. However, existing tools mostly focus on low-level grammar error correction, rather than enhancing users' writing styles at the cognitive level [3, 7]. The concept of style has been used in psychological studies to reflect individual differences in learning and behavior. For instance, people tend to be more humorous in online dating, professional in business and literate in early childhood education (as illustrated in Figure 1). New writing assistance tools are needed to create an active, constructive and effective learning environment for learners to analyze and compare different writing styles, and adapt to a target style accordingly.

In this work, we present a novel computational approach to enhancing personalized cognitive learning experience. Built upon technology that reads, understands, learns, reasons, and interacts, the *Cognitive Learning* system is designed to transform the learning experience to be more effective and meaningful. The system provides a perfect fusion of vividly visualized style features and principles along with cherry-picked examples, which together can shape and drive individualized learning suited to each person. By mimicking the masters of writing through the system, a user can glean a deeper understanding of how their sentence structure works, pick up the style of the writer, and achieve good taste and growth. We demonstrate the effectiveness of our system in a scenario of learning from William Shakespeare.

In summary, our contributions are three-fold: (1) A computational method to automatically apply the look and feel of a master's writing to a user's input to assist in their mimic writing. (2) A visual analytics mechanism to help users understand and compare distinct multi-level differences between one target writer's writing and their own to help users immediately pick up the style of the masters. (3) A computational method to identify a small but optimal set of informative examples to help users maximize their learning outcomes at a minimum cost.

COGNITIVE LEARNING

The target audience of our Cognitive Learning system are people who want to enhance their writing skills and styles by learning from the masters of writing. A user's initial writing style is considered as the *source style* and the style of the master he or she wants to learn is referred as the *target style*. Given the user's input and a target style, the system first transfers the source style into the target style based on its underlying model powered by deep learning techniques and language translation

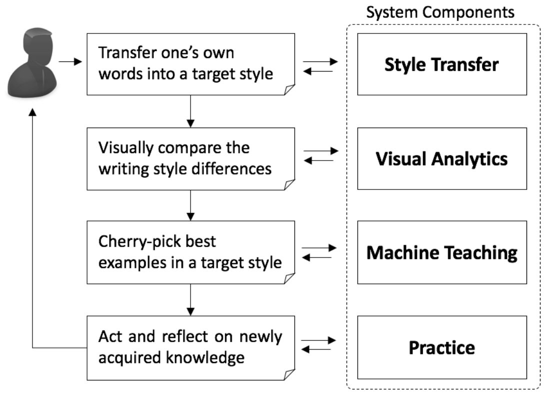

Figure 2: Overview of the system.

Modern Writer: "I love you."
Shakespeare: "I love thee."

Modern Writer: "Oh, I want to talk to you!"
Shakespeare: "O, i will speak to you!"

Modern Writer: "Madam, I wish you all the best."
Shakespeare: "Madam, I desire your holy wishes."

Sidebar 1: Examples of transferring the writing style of a modern writer to Shakespeare's using our sequence to sequence deep learning model.

techniques. The system also performs stylometry analysis on the writings of the source and the target, and visualizes the analysis results in a comparative graph visualization. Furthermore, the system automatically selects the informative and representative examples in the target style for the learners using machine teaching techniques. Finally, the system provides users with several test sentences as an assessment of their learning progress. An overview of our proposed system is shown in Figure 2.

Automatic Style Transfer. This module is trained using a sequence to sequence deep learning model [4]. To prepare the training data for the sequence to sequence model, we propose a novel approach that generates morphologically and syntactically varied sentence pairs with the least semantical loss. For example, to create a parallel document dataset between Shakespeare and a modern English writer, language translation techniques [5] are used to first translate the sentences of Shakespeare into a non-English language (e.g., French) and then translate the sentences back into English. In this way, the system is able to transform Shakespeare's sentences into more natural writings without altering their meaning (as shown in Sidebar 1). The inter-translation language can be chosen such that it sacrifices the least semantic precision for morphological and syntactic naturalness.

Visual Stylometry Analytics. The system performs stylometry analysis on the writings of the two or two sets of writers on different granularities, including *Emotion*, *Syntactic style*, *Cognitive style*, and *Lexical style*. Emotion features capture the proportion of sentences contain the 5 basic emotions: Anger, Disgust, Fear, Joy and Sadness, and are extracted using emotion analysis techniques [6]. Syntactic style features deal with the structure and representation of one's writing, which include: the proportion of long sentences (larger than 15 words), sentences contain apostrophe, hyphen, quote, exclamation mark, question mark, and sub-sentences (comma or semi-colon), long word (larger than 10 characters), multi-syllables words (larger than 1 syllable), and complicated sentences (Flesch-Kincaid grade level larger than 9). Cognitive style features are extracted using the Linguistic Inquiry Word Count (LIWC) [2], which classifies the words into dozens of linguistic and psychological categories that tap social and cognitive processes. Cognitive style features used in this work include: the proportion of sentences containing 1st person, time, certainty, and certainty indicators, etc. Lexical style features capture one's characteristics in word usage (top 10 words from each or each sets of writers). The system presents these multi-level stylometry analysis results in a comparative graph visualization by extending the conventional parallel coordinates visualization [1]. In our design (shown in Figure 3), two bipartite graph visualizations are drawn side by side to support direct comparison of the two writers. Each bipartite graph displays the associations between various emotions and style features, where the vertical stacked bars encode the distributions of the emotion types or style features, and curves in between encode the joint distributions of emotion types and style features. Bars and curves are colored by the emotion types to allow visual tracking of associations. The system supports advanced highlighting and linking interaction of the two bipartite graphs to help users explore the similarities and differences of the two or two sets of writers across emotion types and style features. For example,

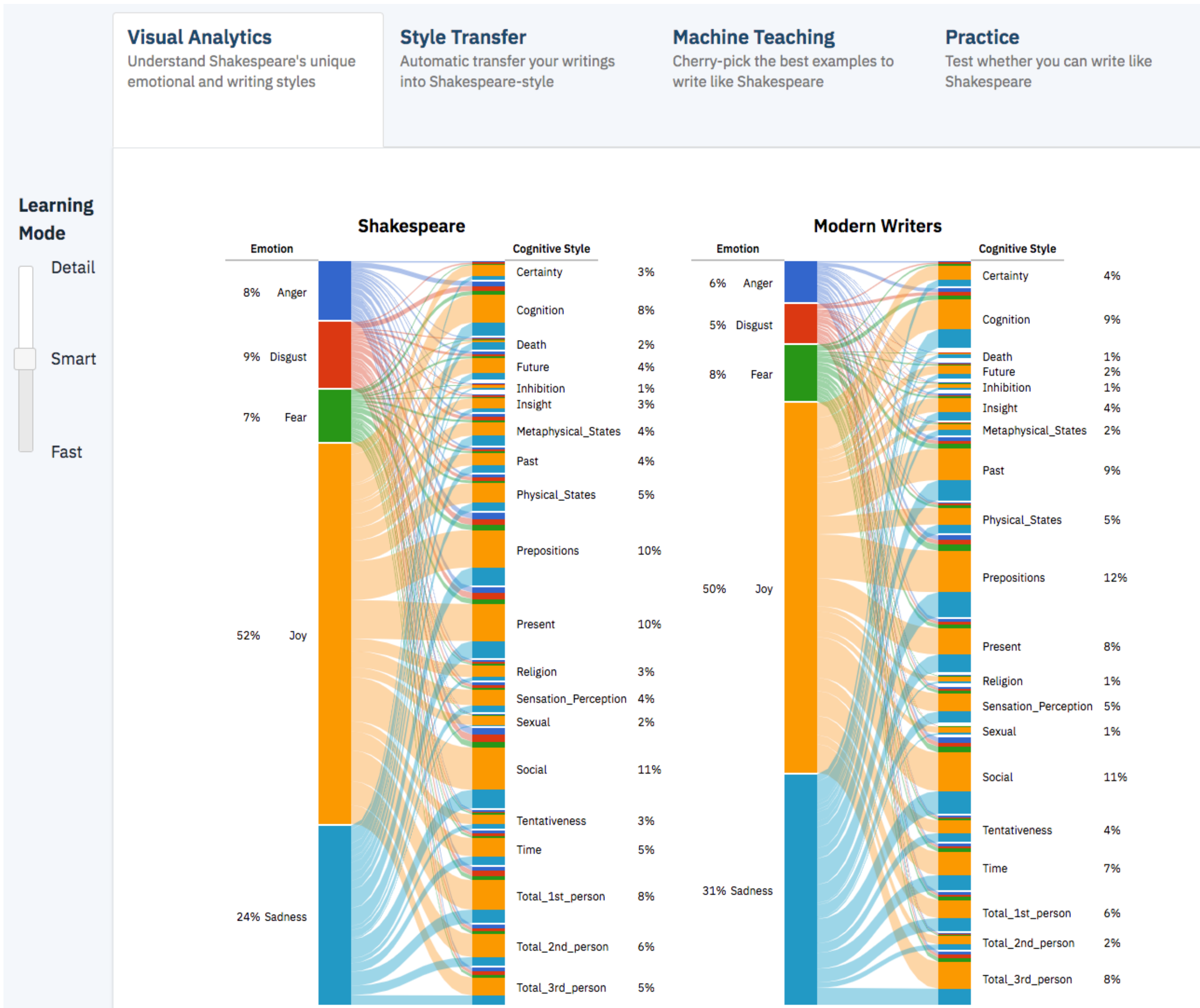

Figure 3: Cognitive Learning interface (the Visual Analytics module). (Left) Emotions, selected style features and their associations derived from the writings of the target writer (Shakespeare). (Right) Emotions, selected style features and their associations derived from the writings of the reference writer (modern writers). Three learning modes are provided to allow users to view syntactic style features in the *Fast* mode, cognitive style features in the *Smart* mode, and lexical style features in the *Detail* mode.

when users hover the Sadness emotion bar segment of the target writer (e.g. Shakespeare), the style features that are associated with Sadness emotion will be simultaneously highlighted in both graph visualizations, while the other irrelevant associations will be automatically hidden (as shown in Figure 4).

Machine Teaching and Practice. Some learners are more inductive than deductive reasoners who learn better from examples than principles. To select an optimal set of massive examples for users to learn in a short period of time, a machine teaching model is trained with a tremendous amount of data to distinguish between the writing styles of well-known writers. Machine teaching [8] is an inverse problem to machine learning, which is used to reverse-engineer the optimal examples for learning. Given the target style and the data on which the model has been trained, the machine teaching model selects the optimal subset of examples (shown in Sidebar 2) that are as informative and powerful as the original training set. These representative examples lead to comparable learning performance to randomly selected cases whose size needs to be orders of magnitude larger. In addition, the system also provides learners with several test sentences as an assessment of their learning progress. All test sentences are intentionally chosen using the machine teaching-based method to see if learners can correctly identify writings from the target or target sets of writers by catching their distinctive writing styles. Learners will read the test sentence and choose whether it is a writing from the target writer or not. The system will validate the correctness of learners's answers and provide feedback accordingly.

“Give signs, sweet girl, for here are none but friends, What Roman lord it was durst do the deed: Or slunk not Saturnine, as Tarquin erst, That left the camp to sin in Lucrece' bed?” — Shakespeare

“O, I would thou didst, So half my Egypt were submerged and made. A cistern for scaled snakes! Go, get thee hence: Hadst thou Narcissus in thy face, to me Thou wouldst appear most ugly.” — Shakespeare

“As an officer of a marching regiment, ordered to rejoin immediately, he must flesh his sword in lather first for he had found no razor strong enough and postpone the day of riches till the golden date of peace.” — a modern writer

“My gaze was rivetted on a pair of boots, fixed in a ledge with horse-shoe bays; on the sole of one I perceived a cross of metal inlaid; I drew nearer to see it more closely, when something fell over my head.” — a modern writer

Sidebar 2: Representative Shakespeare's and modern writers' sentences selected by our machine teaching model.

SCENARIO: HOW TO BECOME WILLIAM SHAKESPEARE

Our system has been implemented as a web application using Javascript and HTML5. The sequence to sequence model for Style Transfer has been deployed as a REST API. Node.js is used to setup up the server and handle the request of Style Transfer. The front end is developed using D3.js, Bootstrap framework and IBM Carbon Design System. To illustrate the capability of Cognitive Learning, we load the complete works of William Shakespeare into our system. Here we describe a scenario of learning from Shakespeare using our system.

Suppose Sophia is a student who wants to improve her writing styles by mimicking Shakespeare. To start with, Sophia went to the Style Transfer module and typed a few sentences. For example, “I love you”. With a single click, the system automatically transfers her input into Shakespeare's writing style, “I love thee”. She then tried another sentence “Oh, I want to talk to you!” and found that Shakespeare would write “O, i will speak to you!” Clearly she observed some interesting style differences between Shakespeare's and the user's own writing. To learn more about such differences, Sophia then looked at the Visual Analytics module. The system quantifies writing styles using various metrics detected from input texts, and visualizes the differences in a way that enables her to learn very quickly and efficiently. In particular, she saw emotion features and different levels of style features from both Shakespeare and modern English writers. The associations between these features are linked interactively to allow

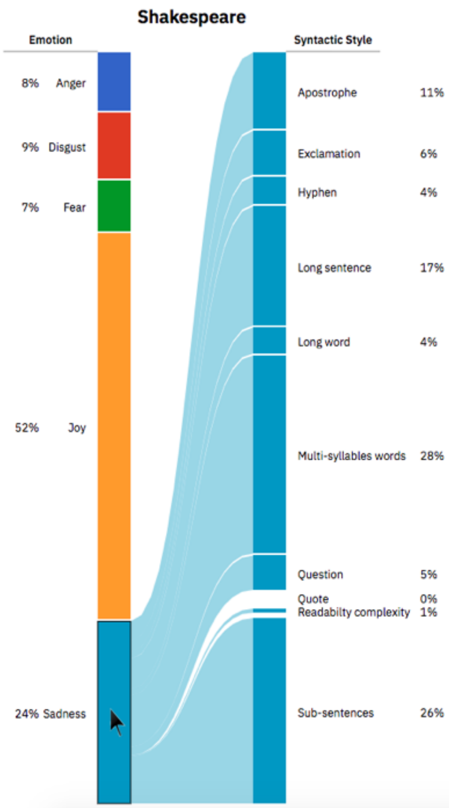

Figure 4: Drilling down into the *Sadness* emotion of Shakespeare's writing. The style features associated with the *Sadness* emotion are highlighted while the other irrelevant associations are automatically hidden.

direct exploration and comparison. For example, She can see that Shakespeare's work tends to be less sad as compared to modern writers. She can focus on those sad sentences and see how the style features differ between Shakespeare's work and modern writers (Figure 4). She found that Shakespeare uses far more apostrophe but less quote in his writings. The system provides three learning modes for exploring different levels of style features. Sophia switched from syntactic style features in the *Fast* mode to cognitive style features in the *Smart* mode. She observed that Shakespeare's work tends to use less past tense, but more 1st and 2nd pronouns, maybe because many of his works are in the format of play. Finally, Sophia checked the word usage in the *Detail* mode, where she can see that Shakespeare used some unique words such as o, thee, thou, etc. To better understand Shakespeare's writings, Sophia went to the Machine Teaching module, where the system creates a shortcut for her by providing the most informative learning cases selected using machine teaching techniques (shown in Sidebar 2). In the end, Sophia can participate in a practice that tests how well she have learned from Shakespeare.

CONCLUSION AND FUTURE WORK

In this work, we present a computational approach that allows learners to have fast but effective learning experience with the help of one click style transfer, one glimpse visual analytics, and one shortcut curriculum design. Mimicking masters of writing such as William Shakespeare is only a small step along the important journey to cognitive learning. In the future, we plan to conduct formal user studies to evaluate the usability of our system. Furthermore, our system can be applied to various domains, such as online dating, business and early childhood education, no matter one wants to be more humorous, professional or literate.

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