Research Statement

Wei Xu, Assistant Professor, Department of Computer Science and Engineering, The Ohio State University

I want to tackle a grand challenge in AI and natural language processing (NLP) to make computers understand the complex meaning that is expressed in different human language forms. I design **machine learning** models for **natural language generation** with stylistic variations (e.g., generating simpler versions of newswire texts that express the same meaning, so that even a 10-year old can read them) and learning semantics from large data for **natural language understanding** (e.g., recognizing texts that have the same meaning to track down the spread of misinformation). These two sides of my research are very connected from the data point of view, but explore very different learning algorithms. More generally, I am interested in creating robust technologies to process not only well-edited text, such as news, but also noisy **user-generated data**, such as that found in social media or biomedical lab instructions.

1 Natural Language Generation / Stylistics

The core of most text-to-text generation problems is sentential paraphrasing with stylistic constraints, which can be thought of as monolingual machine translation (e.g., English→Simple English). While automatic bilingual machine translation (e.g., German→English) has become better and better, natural language generation remains one of the most challenging research problems in NLP due to the complexity of the human editing process, the limited amount of high-quality data, and difficulties in evaluation.

Take **text simplification** (Figure 1), my favorite generation task, for example, it involves a delicate mixture of lexical and syntactic paraphrasing, compression, and sentence splitting in order to make text easier to read and understand. It is practically useful for children[1] and people with disabilities (e.g., deaf, dyslexia, autism) as well as many others to read medical or legal documents, etc. Simplification was popularly studied between 1997 and 2004 from the cognitive science perspective with rule-based methods, and then revived in 2010 because of the availability of Simple English Wikipedia and the development of statistical methods. However, in Xu et al. 2015 [2] and Xu et al. 2016 [3], I uncovered and analyzed two severe problems of the falsely assumed quality of the then-standard dataset derived from Wikipedia data and the evaluation setup using the BLEU [4] metric.[2] To address these issues, I created a new tunable metric, SARI [3], which is effective as a learning objective for training both statistical and neural machine learning models, and al-

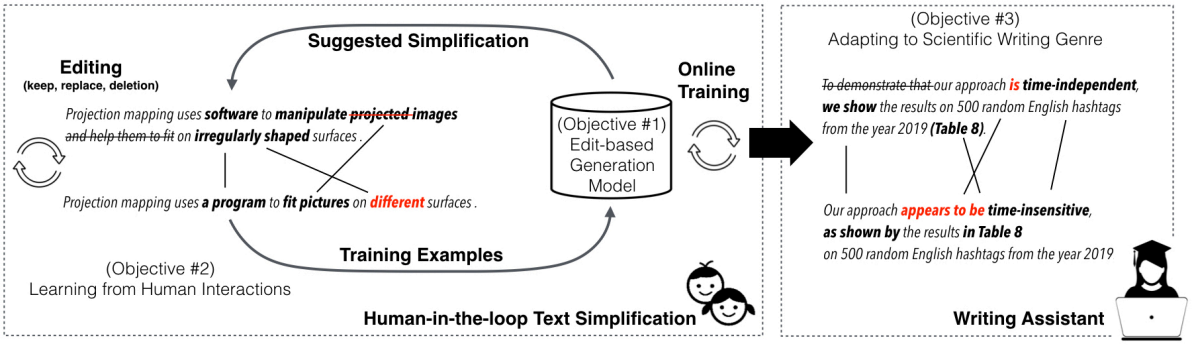

Figure 1. Illustration of my research plan on natural language generation, including three research objectives and two educational applications: (a) text simplification for children and (b) scientific writing for college students. The methodology is general and applicable for other generation tasks and text genres. The example editing adjustments shown in red can be collected from user interactions or simulated from static text corpora.

[1] According to a report released by U.S. Department of Education [1], more than 65% of 8th graders in American public schools are not proficient in reading and writing.

[2] BLEU is the most commonly used evaluation metric for automatic machine translation.

lows researchers to quickly iterate model designs. SARI is now implemented by the Google AI group in TensorFlow, a popular open-source library for training deep learning models. SARI has also been used for different natural language generation tasks, including sentence fusion, style transfer, and text-to-animation generation. We also introduced a high-quality crowdsourced corpus and a professionally edited simplification corpus [2] in collaboration with an education startup company, Newsela, which are now the standard benchmark used by research groups worldwide [5, 6, 7, 8, and others].[3] The automatic simplification system I designed [3] by optimizing syntactic machine translation models toward SARI is currently one of the best performing methods. More recently, my PhD student Mounica and I proposed a unified neural ranking model [9] with a Gaussian-based vectorization layer. It achieves state-of-the-art performance on three lexical simplification tasks, which ensemble a fast lightweight pipeline and will enable the development of a real-time interactive system (see future work below).

Besides simplification, I have worked on a variety of other natural language generation problems, ranging from **error correction** [10, 11], to **user's stylistic preferences** [12] and **paraphrase generation** [13, 14]. Each touches on different learning algorithms with different constraints and data sources. Currently, I am working on: (i) data augmentation for sequence-to-sequence models to combine different generation operations as part of a collaborative research project with HCI and deaf education experts, supported by NSF's Cyberlearning program; (ii) multilingual text simplification that simplifies inputs while retaining important information to help machine translation [15] and information extraction [16, 17, 18, 19, 20, 21, 22], as one of our innovations for the new IARPA's BETTER program; (iii) document-level generation to address the lack of research on how neural network models handle cross-sentence information and document structure [23]; and (iv) better semantic models and crowdsourcing methodology to create larger and higher-quality training data for generation (more details in Section 2). In particular, I found these research directions exciting for **future work**: (i) interactive and human-in-the-loop natural language generation (prototyped in [14]) that can effectively learn and incorporate user representations into generation for quality control and personalization; (ii) more controllable and interpretable neural generation models that can mimic human editing actions explicitly with specific paraphrasing modules, instead of the black-box sequence-to-sequence models; (iii) more complex natural language generation scenarios, including unsupervised and semi-supervised generation which are especially useful for multilingual cases, and new task of scientific writing and revisions. My **long-term goal** is to develop reading and writing assistant technologies, and to find more human-computer interaction (HCI) and education experts to collaborate with.

2 Natural Language Understanding / Semantics

My approach to natural language understanding is learning and modeling very-large-scale paraphrases [24]. Intellectually, I think that paraphrases are fascinating, allowing me to focus on elegant and scalable machine learning models for inferring semantic relationships between words and sentences. This research direction sprouted from my early work on automatic text summarization [25, 16], and is in the same vein as other great PhD theses and research on paraphrases, including from Regina Baziley [26], Chris Callison-Burch [27], and Percy Liang [28]. But, I take an entirely different approach to obtain paraphrases on a much larger scale and with a much broader range than any previous work, essentially by developing more robust machine learning models and leveraging social media data. These paraphrases can enable natural language processing systems, such as machine translation or automatic knowledge base construction, to handle rare words (e.g., `NetsBulls series` ↔ `Nets and Bulls games`), idiomatic expressions (e.g., `gets the boot from` ↔ `has been sacked by`), abbreviations (e.g., `Man City` ↔ `Manchester City`), language shifts (e.g., `is bananas`

[3] See NLP Progress for the datasets and the current state-of-the-art for the most common NLP tasks, including text simplification research progress written by Fernando Alva Manchego: `http://nlpprogress.com/english/simplification.html`

↔ `is great`), and other lexical variations (e.g., `oscar nom'd doc` ↔ `Oscar-nominated documentary`).

One of my ambitious plans is to construct **LanguageNet**[4] (Figure 2), a large-scale database for human language that continuously updates with paraphrases extracted from timely social media and news streams. To this end, we designed a series of unsupervised [11] and supervised learning methods for paraphrase identification from social media data (also applicable to question/answer pairs [29] for QA systems), ranging from multi-instance learning [30], to subword neural network models [31] and tree LSTM [29]. Our recent work [32] demonstrated the feasibility of obtaining paraphrases continuously from tweets and news that contain the same web links and trending topics. Our newest model using neural semi-Markov conditional random fields can align semantically similar text units across sentences more accurately [33]. We have also been working on improving crowdsourcing techniques to collect human-labeled data for training deep learning models to identify semantic relations. We are currently in the third iteration to refine our methods (first version released as a shared task at SemEval 2015 [34]), and we just collected the largest sentential paraphrase corpus to date of over 130,000 English sentence pairs this summer. While researchers have long recognized the importance of modeling semantic relations between sentences and developed various datasets, none of the existing datasets (e.g., MSRP [35], STS [36], SNLI [37]) have the same quantity, quality, and naturalness. I believe this **multi-year ongoing project** will fill the void and lead to significant impacts in natural language processing (NLP) research, analogous to how the ImageNet[5] project of labeled images, led by Feifei Li, has transformed computer vision research. I plan to extend the LanguageNet to include more different languages, and to support tracking information spread across multiple social media platforms. This line of my research is supported by a NSF CRII award and a research subcontract from the DARPA SocialSim program. It is also closely related to paraphrase generation, a popularly studied natural language generation (Section 1) task but with no existing large high-quality data. Other **future work** includes utilizing this new continuously updating semantic resource to improve **information extraction** [16, 17, 18, 19, 20, 21, 22] systems, as well as other NLP systems, to dynamically adapt to new emerging or low-frequency words, event phrases, and entities by pivoting through alternative paraphrases (e.g., `poshtel` ↔ `posh hostel` ↔ `luxury hostel`).

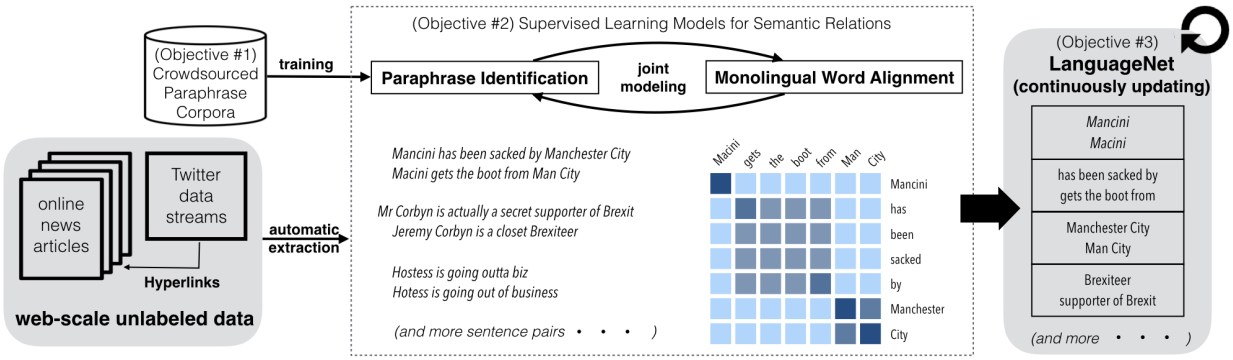

Figure 2. Illustration of my approach for learning large-scale paraphrases, designing automatic semantic models, and constructing a timely semantic resource, LanguageNet. Paraphrases are crucial for natural language understanding, such as in IBM's Watson QA system [38, 39] to connect questions and answers (e.g., `Who is the CEO that is stepping down from Boeing?` → `after Boeing Co. Chief Executive Harry Stonecipher was ousted from`).

[4] LanguageNet is one of the eight winning projects of the AI for Everyone Award in 2018.

[5] `https://en.wikipedia.org/wiki/ImageNet` *"AI researcher Fei-Fei Li began working on the idea for ImageNet in 2006. At a time when most AI research focused on models and algorithms, Li wanted to expand and improve the data available to train AI algorithms."*

3 Noisy User-generated Data / Social Media

For AI to truly understand human language and help people (e.g., instructing a robot), I think, we ought to study the language people actually use in their daily life (e.g., posting on social media), besides the formally written texts that are well supported by existing NLP software. I thus focus on specially designed learning algorithms and the data for training these algorithms to develop tools to process and analyze noisy user-generated data. I work a lot with Twitter data [25, 11, 40, 41, 42] because it is publicly available in large quantity and as it is easy for other researchers to access and reproduce results. Social media also contains very diverse languages for studying stylistics (Section 1) [12] and semantics (Section 2) [30, 34, 32], carrying information that is important for both people's everyday lives and national security. In the past three years, with my students, I have expanded my scope to cover a wider range of user-generated data, including biology lab protocols [43], Quora [29], Urban Dictionary, StackOverflow, and GitHub [44].

For example, in our ACL 2019 paper [45], we presented a novel neural ranking model (Figure 3) to analyze the semantic meaning of hashtags, which are often used in social media and carry important information. The open-source tool we released, **HashtagMaster**, can break hashtags into meaningful word sequences (`#IRGCOUTOFIRAQ` → `IRGC out of Iraq`[6]) with 92–95% accuracy, several points better than the previously available Microsoft Word Breaker API. Our proposed pairwise ranking model with an adaptive multi-task learning objective can capture the subtle differences between possible word sequences and better handle non-standard spelling variations, in contrast to the standard approaches used in previous work. This is an improvement and extension of the original neural ranking algorithm we proposed to measure the complexity of words/phrases [9] for text simplification (Section 1). Since the model is not language dependent, I plan to extend HashtagMaster to handle hashtags written in other languages, such as Arabic, and to introduce it to other research communities that often analyze hashtags, such as communication and political science.

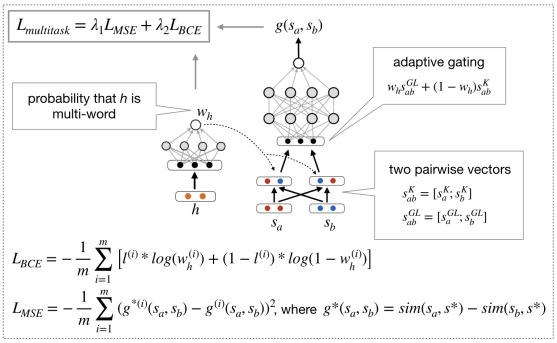

Figure 3. Pairwise neural ranking models with adaptive multi-task learning. Given two candidate segmentations s_a and s_b of hashtag h, the goal is to predict the segmentation's relative quality score g.

Another recent work of ours was on **Biomedical Lab Protocols**, published at NAACL 2018 [43], where we looked into automatically extracting machine-readable representations from biomedical lab procedures written in unstructured natural language text. Our methodology has since been picked up by researchers at UMass/MIT and extended to materials science procedural texts. I am currently working with students and collaborators to enlarge the dataset and plan to organize a shared task at the **Workshop on Noisy User-Generated Text (WNUT)** to facilitate research and development for scientific experiment automation. The WNUT Workshop is an annual one-day event I co-founded and have co-organized since 2015. It collocates with top NLP conferences (ACL/EMNLP/NAACL/COLING) and gathers around 100∼150 researchers worldwide each year.

I am interested in instructional or procedural language, as it is understudied in the NLP research literature, yet is very important for future research in human-computer and human-robot interactions. Another exciting aspect of research on user-generated data to me is that I can work not only with human languages, but also with metadata and non-language data (e.g., programming code). This opens up a lot of opportunities to develop novel machine learning models, and to collaborate with people on interdisciplinary projects.

[6] IRGC, the Islamic Revolutionary Guard Corps, is a branch of the Iranian Armed Forces and designated as a terrorist organization by the government of the United States.

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