Show and Write: Entity-aware News Generation with Image Information

Zhongping Zhang  Yiwen Gu  Bryan A. Plummer
Boston University
{zpzhang, yiweng, bplum}@bu.edu

Abstract

Automatically writing long articles is a complex and challenging language generation task. Prior work has primarily focused on generating these articles using human-written prompt to provide some topical context and some metadata about the article. That said, for many applications, such as generating news stories, these articles are often paired with images and their captions or alt-text, which in turn are based on real-world events and may reference many different named entities that are difficult to be correctly recognized and predicted by language models. To address these two problems, this paper introduces an Entity-aware News Generation method with Image Information, ENGIn, to incorporate news image information into language models. ENGIn produces news articles conditioned on both metadata and information such as captions and named entities extracted from images. We also propose an Entity-aware mechanism to help our model better recognize and predict the entity names in news. We perform experiments on two public large-scale news datasets, GoodNews and VisualNews. Quantitative results show that our approach improves article perplexity by 4-5 points over the base models. Qualitative results demonstrate the text generated by ENGIn is more consistent with news images. We also perform article quality annotation experiment on the generated articles to validate that our model produces higher-quality articles. Finally, we investigate the effect ENGIn has on methods that automatically detect machine-generated articles.

1. Introduction

Language modeling is a central problem in natural language processing with wide-ranging applications such as machine translation [2, 35, 36, 40], question answering [7, 20, 34, 45], article generation [5, 30, 31], text summarization [22, 49], among others. In early work [1, 17, 21], the dominant approach to train language models is collecting data and training models for specific tasks, which works well under particular data distribution and cases, but found challenging to generalize to out-of-distribution inputs. More recently, language generators have shifted to finetuning pretrained large-scale language models on domain-specific data such as news articles [5, 30, 31, 50]. These methods can generate news either via unconditional sampling given the first few sentences of news [30, 31] or via conditional sampling given the news metadata such as title, author, publishing date [5, 50].

There are two important challenges that remain unexplored by prior work. First, prior work for article generation performs text-only language modeling (Figure 1(a)), ignoring embedded images in the articles that may provide additional insights. Second, these methods only implicitly model named entities that commonly appear in long articles like organizations, places, and dates to indicate the background of an event. These named entities are critical to accurately modeling a long article, but it often is not known what named entities may appear at test time. Effectively leveraging named entities not only improves the accuracy...
of word prediction but also makes articles such as the news or Wikipedia more consistent with the other metadata like image content.

To address these two challenges, we propose Entity-aware News Generation framework with Image iNformation (ENGIN), which incorporates image information and an entity-aware mechanism for article generator as illustrated in Figure 1(b). We observe that named entities indicate important contextual information about the events related to a news report. However, when training a language model using prior work, named entities are modeled together with the other text, and the language model may find it difficult to distinguish entity names from the other text in articles. To solve this issue, we propose an entity-aware mechanism to help ENGIN recognize and predict named entities. Specifically, we insert special tokens after each entity name to indicate its entity category. ENGIN models the named entity with its entity category jointly. An additional benefit brought by our Entity-aware mechanism is the named-entity recognition (NER) ability, i.e., our model not only recognizes and predicts the entity names but also predicts the entity category simultaneously.

As shown in Figure 1, the images and their captions can also contain important events or key figures associated with an article. Providing a list of named entities for generating an article does require a small overhead and boost performance, but we find that we can extract that information automatically without the need for manual input. Motivated by the intuition that large vision-language models such as Contrastive Language-Image Pretraining (CLIP) [29] have seen various named entities during training, we design a framework that automatically selects a set of likely named entities from an image (see Section 3 for more details). Figure 2 presents the overall pipeline of ENGIN.

In summary, the contributions of this paper are:

- We propose an entity-aware language model called ENGIN for news article generation. Compared to existing models focusing on text-only documents [5,50], ENGIN effectively leverage the embedded images in news articles and generate higher-quality articles exploiting image information from the articles.
- We propose an Entity-aware mechanism to help language models better recognize and predict named entities, which inserts the entity category after each entity name, boosting performance.
- Our approach is evaluated through extensive experiments on GoodNews [4] and VisualNews [24]. Notably, ENGIN-XL with 1.5B parameters outperforms the GPT-J model [43] with 6B parameters, improving roughly 2.5 perplexity points on both datasets.
- We perform article quality annotation experiment to verify that ENGIN produces more realistic news compared to prior work [31, 50]. This suggests that our model may help provide additional training data for learning a more powerful machine-generated news detectors.
2. Related Work

**Language Models** for a document can be represented by the joint probability of sequences of words [3], where the probability of the next word is predicted conditioned on previous words. Much early work for language models has been done using Recurrent Neural Networks (RNN) or Convolutional Neural Networks (CNN) to address sequential information [6, 16, 18, 27, 44, 46]. Recently, the Transformer [41] was proposed to address the vanishing gradient and loss of information issue in long sequences. The current state-of-the-art in news article generation produces text using large-scale generative pretrained transformer models, which can be divided into two categories: unconditional text generation [30, 31] and conditional text generation [5, 50]. Generating news articles via unconditional samples has been shown to be less effective because the models may interpret the first sentence of news as a tweet and start posting responses [5]. To enable controllable news generation, GPT3 [5] has been used to generate articles conditioned on the titles of news, and Grover [50] learned to decompose news into separate parts and generates articles conditioned on the metadata like the author or news organization. In this paper, we further explore the effect of visual information and named entities for controllable generation. Specifically, ENGIN produces news conditioned on both the metadata of news like prior work and the visual information extracted from news images, with special care for explicitly extracting and modeling named entities.

**News Image Captioning** are designed to caption images based on news articles and images. Early approaches generated news image captions by extracting text from articles, such as retrieving the most representative sentence in the article [9] or using n-gram models to combine existing phrases [38]. To effectively leverage the visual and language representations, Ramisa et al. [33] proposed an end-to-end framework that takes the concatenation of article and image features as input and outputs captions by an LSTM decoder. However, these approaches failed to predict named entities that were not seen during training. Thus, more recent work has included an entity-aware mechanism [4, 24, 39] to more accurately model these elements. In this paper, we effectively leverage the inputs and outputs of these papers, i.e., our paper focuses on article generation based on news images and captions rather than caption generation based on news images and articles.

**Machine-generated Text Detection** is a task that determines whether a text document is written by human or machine. Current strategies include analyzing words distribution statistically [11], adapting generator for discrimination [50], detecting visual-semantic inconsistencies [37], and finetuning pretrained models [25] on domain-specific data. Specifically, GLTR [11] inspects the visual footprint of automatically generated text. It is based on the assumption that a language model always uses the most likely words at each position according to the learned probability distribution during the training phase. In contrast, human writers more frequently select words that are unpredictable but make sense to the domain. Grover [50] outperforms GPT2 in generating fake news, which in turn was used to train a powerful machine-generated text detector for news articles. DIDAN [37] looks for mismatches between named entities in news articles and their image captions, which helps motivate taking more care to ensure named entities are well represented in our model. In our paper, we apply OpenAI’s machine generated text detector based on RoBERTa [25] as our machine discriminator due to its powerful performance on GPT2 [31] detection.

3. ENGIN: Entity-aware News Generation with Image Information

The goal of our task is to generate news articles via conditional samples. As shown in Figure 1, the standard input is metadata of news such as title, domain, publish date and output is the corresponding news article. In this paper, we propose ENGIN, which leverages image information and entity-aware mechanism to generate higher-quality articles. The input to ENGIN consists of both metadata and news image information that is composed of named entities and captions (summarized in Figure 2). We first introduce the language modeling problem in Section 3.1. The method to leverage news image information is then discussed in Section 3.2. Entity-aware mechanism is further presented in Section 3.3. Finally, we summarize the overall learning strategy and details of ENGIN in Section 3.4.

3.1. Language Modeling

Given a set of documents \( \{x_1, x_2, ..., x_n\} \) each consists of variable length sequences of symbols \( \{s_1, s_2, ..., s_m\} \), the statistical language model of a text document \( x \) can be represented by the product of the conditional probability of next symbol given all the previous ones [3]:

\[
p(x) = \prod_{i=1}^{m} p(s_i | s_1, ..., s_{i-1})
\]

where each symbol \( s_i \) is processed uniformly and the document \( x \) is viewed as an unstructured text field (also referred as body field later). Language models based only on Eq. 1 produce news articles via unconditional samples. As a result, these models cannot output controllable generation [15]. For controllable generation, the language model can be formulated by the joint distribution of separate fields decomposed from the news article \( x \) [50]:

\[
p(x) = p(\text{meta}, \text{body})
\]
Help Wanted: Seeking a Sport’s New Face

It is a revolution that started March 5, 2012 — when he signed a contract extension that will keep him in black and gold through 2018. I did not matter that the Pirates were coming off their straight 50-101 loss season, McCutchen saw a bright future where others saw a lost cause. Now the Pirates are heading to the playoffs again, led by an intense, charismatic and talented player who has become the biggest star in a city where Sidney Crosby is the face of the franchise. Though, has 50 CARDINALS World Series EVENT rings locked away somewhere... McCutchen's fingers are currently bare - saw for his wedding band. Maybe that is why he could take a handful of players to move the sport forward, rather than just one. Later become Jeter in October DATE. "He became the face for his..."

Figure 3. Entity-aware mechanism in ENGIN. Each named entity is attached by its corresponding entity category.

where meta field is a data-dependent term consists of a set of subfields. For instance, meta includes date, title, summary in GoodNews [4] and domain, date, topic, title in VisualNews [24]. Thus, we model \( x \) by:

\[
p(x) = p(\text{body})p(\text{meta})
\]

According to Eq. 3, we introduce special tokens <start-\( \tau \>> and <end-\( \tau \>> to indicate the boundaries of field \( \tau \). The content of a target field \( \tau \) is sampled from the model starting with <start-\( \tau \>> and ending with <end-\( \tau \>>.

3.2. Extracting Information from News Images

One of the advantages of ENGIN over prior work is that we can take advantage of the information provided by news images. The current state-of-the-art that combines the image and language descriptions adopts the Transformer [41] architecture and models the text and image tokens as a single stream of data [32]. However, we found using images directly is less effective in the news setting. Unlike typical image captioning systems, news articles report events happening in the real world and tend not to describe objects in embedded news images directly\(^1\). In addition, methods like [32] take 1024 tokens to encode the image. If we adopt this image encoding, the sequence length of our language models will be doubled and the model weights cannot be initialized from the standard pretrained language models. However, this is not to say the images contain no useful information. Indeed, as illustrated in Figure 1, many images contain information about named entities. Thus, as illustrated in Figure 2, we use named-entities extracted from news images in our model, along with the ground truth image captions directly.

We provide information from news images to our model via a combination of two fields, caption field and named-entity field. We use ground truth news image captions directly as the content of caption field. Below we discuss two ways to build named-entity field.

Oracle Named-entities. This approach assumes we are provided with all the named entities that would appear in news articles. To accomplish this, we extract named entities from news articles using SpaCy [14], which is input directly to our model.

CLIP-based NER. Most existing frameworks extract NER from language inputs rather than an image [23, 48]. However, we note that CLIP [29] was trained on 400 million image-text pairs collected from the Internet, many of which likely contained named entities. As such, we use CLIP to build a visual NER framework. First, we construct the text candidate list for each image by extracting named entities from the news using SpaCy [14]. We then apply CLIP to predict similarity scores between the corresponding image and the candidate entities. Finally, we rank the candidate entities by similarity scores and select top \( k \)\(^2\) entities as the representation of the image, which are then provided as input to our language model.

3.3. Entity-aware Mechanism

As we discussed in the Introduction, effectively generating named entities can make news more accurate since information about these named entities can be encoded and they can help avoid inconsistencies between the visual data associated with a news article and the article body itself. For example, in NBA news, an entity-aware model should be able to predict “Curry” given the previous word “Stephen” while the traditional language models might fail. Existing methods model named entities uniformly with the other text, making the leverage of named entities less effective. To help our language model be aware of named entities, we insert the entity category predicted by SpaCy [14] after each entity name. Then the entity name and its corresponding label are modeled jointly by ENGIN. We visualize our entity-aware mechanism by an example in Figure 3.

3.4. Overall Learning Strategy

Architecture. We build ENGIN using the same architecture of GPT2 [31]. Following GROVER [50], we propose three model sizes: (1) ENGIN-Base has 12 layers and 124 million parameters, on par with GPT2-124M and GROVER-Base; (2) ENGIN-Medium has 24 layers and 355 million parameters, on par with GPT2-355M and GROVER-Large; (3) ENGIN-XL has 48 layers and 1.5 billion parameters, on par with GPT2-1.5B and GROVER-Mega.

Encoding Strategy. Given the image information extracted

---

\(^1\)For example, the language description of the image in Figure 2 is "a baseball player swing a bat at a ball" (by NIC [42]). However, the ground truth caption is "Andrew McCutchen, 27, of the Pittsburgh Pirates is among the heirs apparent to become the next links in a long chain of baseball greats" and the article is discussing Andrew McCutchen’s contract and his future career.

\(^2\)We set \( k \) to 10 in this paper.
from news image, Equation 3 is re-formulated as:

\[ p(x) = p(\text{body}, \text{meta}, \text{vision}) p(\text{meta}, \text{vision}) \]  

(4)

where \text{vision} field consists of \text{caption} field and \text{named-entity} field (from Section 3.2). To sample from Equation 4, we define a canonical order\(^3\) among the fields (or subfields) of news \(\mathcal{F} : \{f_1 < f_2 < ... < f_{|\mathcal{F}|}\}\) and model the news left-to-right in the order using Equation 1: \(s_1, s_2, ..., s_{|\mathcal{F}|}\). If a specific field \(f_i\) is missing, our model will automatically skip that field by introducing the start token of next field \(f_{i+1}\). We illustrate such an example in Figure 2, where ENGIN starts generating the \text{body} field after \text{title} because the \text{summary} field is empty.

**Decoding Strategy.** Likelihood-maximization decoding strategies like greedy search or beam search work well in close-ended generation such as image captions, machine translation, or summarization. However, these methods suffer from the repetitive text problem in open-ended generations like dialog or story generation [12, 13]. Sampling methods [8, 13] are therefore proposed to introduce more randomness and surprise to text generation. In our work, we adopt the top-p sampling (nucleus sampling) method [13] as our decoding strategy for news article generation.

4. Experiments

4.1. Datasets and Experiment Settings

**Datasets.** We evaluate ENGIN on two large-scale news datasets: GoodNews [4] and VisualNews [24]. The GoodNews dataset provides the URLs of news from New York Times ranging from 2010 to 2018. We were able to download 307,286 news articles from the provided URLs. The remaining articles are either broken links or non-English articles. Following the split ratios of [4], we randomly split 15,365 articles in validation set, 30,728 articles in test set, and the rest articles in training set. The VisualNews dataset contains news articles from four news sources: Guardian, BBC, USA Today, and Washington Post. We obtain 582,194 news articles in total after we removed broken links and articles without metadata. Similarly, we get a 491,796 training set, 28,932 validation set, and a 57,889 test set.

**Metrics.** We adopt Perplexity (PPL) to quantitatively evaluate our language models. Perplexity is defined as the exponentiated average negative log-likelihood of a sequence. Given Equation 1, the perplexity of \(x\) is calculated by:

\[ \text{PPL}(x) = \exp \left\{ -\frac{1}{m} \sum_{i=1}^{m} \log p(s_i | s_1, ..., s_{i-1}) \right\} \]  

(5)

\(^3\)We define the canonical order in Goodnews [4] as: domain, date, named-entity, title, caption, summary, body; the canonical order in Visualnews [24] as: domain, date, topic, named-entity, title, caption, body.

\(^4\)The official code of GPT-3 [5] has not been released. We compare ENGIN to GPT-Neo [10], a replication of GPT-3 by EleutherAI, instead.
Table 1. Comparison of different generation methods and model sizes using perplexity (PPL) to measure performance on the GoodNews and VisualNews datasets. ClipNE denotes that we select CLIP-based named entities in named-entity field (described in Section 3.2), NE denotes that we apply oracle named entities in named-entity field. PPL is calculated only on the article body.

| Model Name                  | n\_params | n\_layers | d\_model | n\_heads | GoodNews PPL ↓ | VisualNews PPL ↓ |
|-----------------------------|-----------|-----------|----------|----------|----------------|------------------|
| GPT2-124M [31]              | 124M      | 12        | 768      | 12       | 23.6           | 27.5             |
| Grover-Base [50]            | 124M      | 12        | 768      | 12       | 23.8           | 21.9             |
| GPT-Neo-125M [10]           | 125M      | 12        | 768      | 12       | 27.1           | 29.3             |
| GPT2-124M (Finetuned)       | 124M      | 12        | 768      | 12       | 17.3           | 18.3             |
| Engin-Base (ClipNE)         | 124M      | 12        | 768      | 12       | 14.8           | 16.1             |
| Engin-Base (NE)             | 124M      | 12        | 768      | 12       | **12.0**       | **13.1**         |
| GPT2-355M [31]              | 355M      | 24        | 1024     | 16       | 17.8           | 20.1             |
| Grover-Large [50]           | 355M      | 24        | 1024     | 16       | 18.5           | 16.4             |
| GPT-Neo-1.3B [10]           | 1.3B      | 24        | 2048     | 16       | 15.3           | 15.9             |
| GPT2-355M (Finetuned)       | 355M      | 24        | 1024     | 16       | 13.5           | 14.0             |
| Engin-Medium(ClipNE)        | 355M      | 24        | 1024     | 16       | 11.6           | 12.5             |
| Engin-Medium(NE)            | 355M      | 24        | 1024     | 16       | **9.5**        | **10.2**         |
| GPT2-1.5B [31]              | 1.5B      | 48        | 1600     | 25       | 13.9           | 15.7             |
| Grover-Mega [50]            | 1.5B      | 48        | 1600     | 25       | 14.5           | 12.6             |
| GPT-Neo-2.7B [10]           | 2.7B      | 32        | 2560     | 20       | 13.5           | 14.0             |
| GPT-J-6B [43]               | 6B        | 28        | 4096     | 16       | 11.3           | 11.6             |
| GPT2-1.5B (Finetuned)       | 1.5B      | 48        | 1600     | 25       | 12.6           | 12.4             |
| Engin-XL(ClipNE)            | 1.5B      | 48        | 1600     | 25       | 10.8           | 11.1             |
| Engin-XL(NE)                | 1.5B      | 48        | 1600     | 25       | **8.7**        | **9.0**          |

Figure 5. Ablation results of Engin-Base on GoodNews and VisualNews. Text-only denotes the model focuses only on text information, which is same to finetuned GPT2 model. Cap denotes caption field, EA denotes the Entity-aware mechanism.

Perplexity. Table 1 presents sizes, architectures, and perplexity results of different models on GoodNews [4] and VisualNews [24] test sets. We see that ENGINS of all three model sizes significantly outperform the baselines. On the base size, our model Engin-Base(NE) improves PPL over the original GPT2-124M model by a factor of 2 (23.6→12.0, 27.5→13.1). We draw three major conclusions from Table 1. First, the data distribution still plays an important role. Finetuned GPT2s improve PPL over the original GPT2s. The improvements become less obvious with a greater model size (VisualNews: 27.5→18.3 of base size; 15.7→12.4 of XL size). Second, Engin noticeably improves the performance over finetuned GPTs (4-5 perplexity points on both datasets), which demonstrates the effectiveness of our approach. Third, PPL improves with increased model sizes, indicating that a more powerful generator could be trained with even greater model size.

Parameter Efficiency. Table 1 shows that Engin can achieve a comparable performance with alternative models using much fewer parameters. For instance, Engin-Base(NE) only has 124M parameters but it outperforms the GPT-NEO-2.7B and achieves comparable performance with finetuned GPT2-1.5B (12.0 vs. 12.6 PPL on GoodNews, 13.1 vs. 12.4 PPL on VisualNews). Engin-Medium (NE) model with 355M parameters already outperforms all the baselines including GPT-J-6B. Figure 4 plots the perplexity of language models on two datasets as a function of the number of parameters, further illustrating that Engin models get comparable or better results to alternative methods using far fewer parameters.

Ablation Study. Figure 5 shows ablations of Engin-Base to supplement our analysis. We observe that both the caption and named-entity fields boost performance, revealing that cues from news images can help produce higher-quality articles. Comparing using only captions (Cap) vs. combining them with our Entity-aware mechanism we get a minimum gain of 0.6 PPL, demonstrating its effectiveness.

Article Quality Annotation. Following [5, 19, 50], we ask
Human-written News Article

In 2007, the French industrial designer Jean Louis Iratzoki opened a remote studio in a wood cabin in the foothills of the Pyrenees. His minimalist "refuge" has recently become an unlikely creative epicenter for industrial production on both the French and Spanish sides of the Pays Basque.

At last year’s Maison & Objet design fair, Mr. Iratzoki won plaudits for designing one of the world’s first bioplastic chairs made of a biodegradable plant-based polymer. That shell chair, part of a long collaboration with the Basque furniture brand Aiki, is only one example of Mr. Iratzoki’s determination to promote his native region. (Mr. Iratzoki was born in St. Jean-de-Luz.) He has also recently revamped the brand identity of Cazenave (a Basque chocolate company) and helped design the interiors of a luxurious eco lodge in Saubion, north of Biarritz.

This year, he founded a new practice with a Basque designer of Spanish extraction, Ander Lizaso, with the aim of creating a multipurpose design studio inspired by the French and Spanish sides of the Pays Basque.

ENGIN-generated News Article

Following in the footsteps of his male counterpart, the 2007 French-Spanish architect Jean Louis Iratzoki, whose archives became the subject of last year’s Basque/Francophile Rodeo Drive exhibition, Ander Lizaso, the designer of the Pays Basque label Maison & Objet, has taken on the relatively new mantle of directoire in his own right. This year, he announced the inaugural of his own Design Angeles - in - Motion, the largest design fair for brands of the Basque/Francophone world.

"He’s the one name you know everywhere, " said Lizaso, who came of age as a designer in the city of Aiki during the first boom in construction trade there, selling commissioners as part of the community’s growing business. "And it was the same in France."

Going back to Belgium, where the heritage of the Maison & Objet founders still lies, imbuing his name with its celebrated high culture associations, he explained, the house was fully aware of its Basque roots."

GPT2-generated News Article

Tears eluded Chris Burch and his wife, Susana, when they first set eyes on each other as headwaiter in 1991. They had no idea how they would end up there. But neither did he, not at the time, not even 10 years later. Their friendship would grow into a tentative romance; twice, both of them, over the next 13 years, would fly away from their native Basque region to live and work and play together in New York. Until suddenly they were happily on their own, taking care of themselves. In 2012, with both 40, Burch decided to marry them. Thirty years later, the brothers will go their separate ways: Chris, the artistic director of the Gypsy Rose Lee boutique in the West Village, and Susana, founder and creative director of her own company, Flora Flora, which specializes in floral textiles and ties. "A wedding is an intimate, temporary thing, where people are sending you on your merry way," Chris explains. "You leave with a future and a few words of what you can say. With something you want to do full-fledged – ‘We’re engaged’ or ‘I have a proposal’ – you can’t even focus." The couple recently moved to Miami, where Chris wants to take a nautical theme to Hawaii, where Susana is from. Below, they discuss the undercurrents of their romance as lifelong friends.

GROVER-generated News Article

In both making clothing and politics, Ms. Madrid strives to combine the traditions of dress and activism with the street’s distinct urbanity. She designs a range of products, from T-shirts and tees for millennials, to men’s shirts for families. Everything in both stands as her identity as a designer. “I’m the most passionate person in designing my own clothes because I’m a feminist,” Ms. Madrid said in an interview at a café in town. “I’m very anti-strong men and fat women.”

The 40-year-old mother of two is creating a new business. It’s aiming to combine traditional fashion and activism. She’s hoping to raise money and offer services for political activism in the Basque country - and beyond.

In the past four decades, Ms. Madrid has been involved in social and political activism. She went on hunger strike after she was attacked while in jail. Her goal is to become a national emblem for the Basque country, she said, but she’s not convinced this is a responsibility of the Basque government.

Figure 6. Qualitative examples comparing ENGIN-XL with GPT2-1.5B (Finetuned) and GROVER-Mega on GoodNews. We cut the articles to fit the figure size. The entity names from image information are highlighted in light purple (PERSON tag) and light blue (ORG tag) colors. We can see that the named entities in captions also appear in the human-written and ENGIN-generated articles. In contrast, the GPT2-generated and GROVER-generated articles do not contain the correct entity names corresponding to the image and caption.
We also apply a machine discriminator to detect the generated articles. Specifically, we apply a RoBERTa [25] detector finetuned with the outputs of GPT2-1.5B [31] to detect generated articles. The maximum article length is cut to 512 to fit the model input size. For comparison, we use the same article set from our article quality annotation experiments. The RoBERTa accuracy is shown in Table 2 (b). We observe that the machine discriminator is much better at identifying the machine-generated news, especially for human-written articles, achieving 100% accuracy. We also see that articles produced by ENGIN-XL can be reliably detected by RoBERTa though it gets the lowest accuracy to be distinguished by AMT workers. This can be due to the fact that GROVER-Mega, GPT2-1.5B, and ENGIN-XL all share a similar underlying model architecture. Thus, they may contain enough similarities in the distributional features that are recognized by the machine discriminator.

### Qualitative Results

We provide a qualitative comparison of GoodNews articles in Figure 6. Consistent with our annotation experiment, we compare the human-written article with three machine-generated articles. From the results, we can see that ENGIN-XL model can effectively produce articles with the named entities learned from image information. In contrast, finetuned GPT2-1.5B and GROVER-Mega failed to generate correct named entities in articles. For example, both ENGIN-generated article and the human-written article mentioned “Hean Louis Iratzoki” and “Alki”, which are appeared in the caption. In contrast, articles generated by GPT2 or GROVER are discussing some other names such as “Chris Burch”, “Ms. Madrid”, etc. See the supplementary for additional results and comparisons.

### 4.3. Discussion

**Defending against machine-generated fake news.** In our paper, we mainly investigate modeling machine-generated news, which can be used directly for generation, but also can provide strong language features to support applications like article retrieval. However, actors can also use the same technology to generate fake news by modifying information of specific fields to realize two purposes: monetization (ad revenue through clicks) or propaganda (communicating targeted information) [50]. Therefore, the development of a better news generator can not only help humans write high-quality new articles but also potentially help train a more powerful discriminator. When comparing the results of the RoBERTa detector for GPT2-1.5B and ENGIN-XL in Table 2, we find that only 25% of the articles that were predicted as human written came from the same generation prompts. Thus, the two methods can provide different views given the same prompt, which can provide additional information for training an even more powerful machine generated text detector. We note that our contributions are largely architecture agnostic, so they could be provided as input to RNN-based generators, which may provide a larger distribution shift in the generated articles that may fool a discriminator trained only on Transformer-based outputs.

**Limitations and future work.** We discuss two potential improvements to our work. First, though our method can effectively predict the correct entity names in news articles, their corresponding entity categories might be mistakenly predicted. For example, in Figure 6, the brand name “Alki” is recognized as a city name by ENGIN. Therefore, a more accurate entity-aware mechanism could be developed in future work. Second, the news image information can be further explored. In this paper, we mainly investigate the captions and named entities of news images. However, other information such as the locations of images within articles, low-level image features may also prove useful for news article generation.

### 5. Conclusion

In this paper, we proposed an entity-aware news generation method called ENGIN to address two factors that are unexplored by prior work: news image information and named entities. Concretely, ENGIN produces articles conditioned on both metadata and visual information extracted from news images. Moreover, we introduced an entity-aware mechanism to help ENGIN recognize and predict named entities more effectively. ENGIN outperforms current popular language models using much fewer parameters in quantitative and qualitative experiments on GoodNews and VisualNews. For example, ENGIN-XL outperforms GPT-J by roughly 2.5 perplexity points using only a quarter parameters of GPT-J. The noticeable improvements.
demonstrate that ENGIN can generate articles more accurately and efficiently. The article quality annotation experiment further validates that ENGIN-generated articles have higher quality compared to existing methods.

Acknowledgements. This work was supported in part by DARPA under agreement number HR00112020054.

References

[1] Michael A Alcorn, Qi Li, Zhitao Gong, Chengfei Wang, Long Mai, Wei-Shinn Ku, and Anh Nguyen. Strike (with) a pose: Neural networks are easily fooled by strange poses of familiar objects. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4845–4854, 2019.

[2] Mikel Artetxe, Gorka Labaka, Eneko Agirre, and Kyunghyun Cho. Unsupervised neural machine translation. arXiv preprint arXiv:1710.11041, 2017.

[3] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Janvin. A neural probabilistic language model. The journal of machine learning research, 3:1137–1155, 2003.

[4] Ali Furkan Biten, Lluís Gomez, Marçal Rusinol, and Dimitris Karatzas. Good news, everyone! context driven entity-aware captioning for news images. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12466–12475, 2019.

[5] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. arXiv preprint arXiv:2005.14165, 2020.

[6] Ciprian Chelba, Tomas Mikolov, Mike Schuster, Qi Ge, Thorsten Brants, Philipp Koehn, and Tony Robinson. One billion word benchmark for measuring progress in statistical language modeling. arXiv preprint arXiv:1312.3005, 2013.

[7] Anthony Fader, Luke Zettlemoyer, and Oren Etzioni. Paraphrase-driven learning for open question answering. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1608–1618, 2013.

[8] Angela Fan, Mike Lewis, and Yann Dauphin. Hierarchical neural story generation. arXiv preprint arXiv:1805.04833, 2018.

[9] Yansong Feng and Mirella Lapata. Automatic caption generation for news images. IEEE transactions on pattern analysis and machine intelligence, 35(4):797–812, 2012.

[10] Leo Gao, Stella Biderman, Sid Black, Laurence Goldberg, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, et al. The pile: An 800gb dataset of diverse text for language modeling. arXiv preprint arXiv:2101.00027, 2020.

[11] Sebastian Gehrmann, Hendrik Strobelt, and Alexander M Rush. Gltr: Statistical detection and visualization of generated text. arXiv preprint arXiv:1906.04043, 2019.

[12] Tatsunori B Hashimoto, Hugh Zhang, and Percy Liang. Unifying human and statistical evaluation for natural language generation. arXiv preprint arXiv:1904.02792, 2019.

[13] Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. The curious case of neural text degeneration. arXiv preprint arXiv:1904.09751, 2019.

[14] Matthew Honnibal and Ines Montani. spacy 2: Natural language understanding with bloom embeddings, convolutional neural networks and incremental parsing. To appear, 7(1):411–420, 2017.

[15] Zhiting Hu, Zichao Yang, Xiaodan Liang, Ruslan Salakhutdinov, and Eric P Xing. Toward controlled generation of text. In International Conference on Machine Learning, pages 1587–1596. PMLR, 2017.

[16] Shihao Ji, SVN Vishwanathan, Nadathur Satish, Michael J Anderson, and Pradeep Dubey. Blackout: Speeding up recurrent neural network language models with very large vocabularies. arXiv preprint arXiv:1511.06909, 2015.

[17] Robin Jia and Percy Liang. Adversarial examples for evaluating reading comprehension systems. arXiv preprint arXiv:1707.07328, 2017.

[18] Rafał Jozefowicz, Oriol Vinyals, Mike Schuster, Noam Shazeer, and Yoshikiyo Wu. Exploring the limits of language modeling. arXiv preprint arXiv:1602.02410, 2016.

[19] Sarah Kreps, R Miles McCain, and Miles Brundage. All the news that’s fit to fabricate: Ai-generated text as a tool of media misinformation. Journal of Experimental Political Science, pages 1–14, 2020.

[20] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: a benchmark for question answering research. Transactions of the Association for Computational Linguistics, 7:453–466, 2019.

[21] Brenden M Lake, Tomer D Ullman, Joshua B Tenenbaum, and Samuel J Gershman. Building machines that learn and think like people. Behavioral and brain sciences, 40, 2017.

[22] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence training. arXiv preprint arXiv:1910.13461, 2019.

[23] Jing Li, Aixin Sun, Jianglei Han, and Chenliang Li. A survey on deep learning for named entity recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40, 2017.

[24] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

[25] Jing Li, Aixin Sun, Jianglei Han, and Chenliang Li. A survey on deep learning for named entity recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40, 2017.

[26] Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models, 2016.

[27] Tomas Mikolov, Martin Karafiát, Lukas Burget, Jan Černocký, and Sanjeev Khudanpur. Recurrent neural network based language model. In Interspeech, 2010.
[28] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32:8026–8037, 2019. 5

[29] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*, 2021. 2, 4

[30] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. 2018. 1, 3

[31] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019. 1, 2, 3, 4, 6, 8, 11

[32] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. *arXiv preprint arXiv:2102.12092*, 2021. 4

[33] Arnau Ramisa, Fei Yan, Francesc Moreno-Noguer, and Krystian Mikolajczyk. Breakingnews: Article annotation by image and text processing. *IEEE transactions on pattern analysis and machine intelligence*, 40(5):1072–1085, 2017. 3

[34] Matthew Richardson, Christopher JC Burges, and Erin Renshaw. Mctest: A challenge dataset for the open-domain machine comprehension of text. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pages 193–203, 2013. 1

[35] Felix Stahlberg. Neural machine translation: A review. *Journal of Artificial Intelligence Research*, 69:343–418, 2020. 1

[36] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112, 2014. 1

[37] Reuben Tan, Bryan A Plummer, and Kate Saenko. Detecting cross-modal inconsistency to defend against neural fake news. *arXiv preprint arXiv:2009.07698*, 2020. 3, 7, 8, 11

[38] Amara Tariq and Hassan Foroosh. A context-driven extractive framework for generating realistic image descriptions. *IEEE Transactions on Image Processing*, 26(2):619–632, 2016. 3

[39] Alasdair Tran, Alexander Mathews, and Lexing Xie. Transform and tell: Entity-aware news image captioning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13035–13045, 2020. 3

[40] Ashish Vaswani, Samy Bengio, Eugene Brevedo, Francois Chollet, Aidan N Gomez, Stephan Gouws, Llion Jones, Łukasz Kaiser, Nal Kalchbrenner, Niki Parmar, et al. Tensor2tensor for neural machine translation. *arXiv preprint arXiv:1803.07416*, 2018. 1

[41] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017. 3, 4

[42] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3156–3164, 2015. 4

[43] Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. https://github.com/kingoflolz/mesh-transformer-jax, May 2021. 2, 6, 11

[44] Tian Wang and Kyunghyun Cho. Larger-context language modelling. *arXiv preprint arXiv:1511.03729*, 2015. 3

[45] Jason Weston, Antoine Bordes, Sumit Chopra, Alexander M Rush, Bart van Merriënboer, Armand Joulin, and Tomas Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. *arXiv preprint arXiv:1502.05698*, 2015. 1

[46] Will Williams, Niranjani Prasad, David Mrva, Tom Ash, and Tony Robinson. Scaling recurrent neural network language models. In *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5391–5395. IEEE, 2015. 3

[47] Thomas Wolf, Julien Chaumond, Lysandre Debut, Victor Sanh, Clement Delangue, Anthony Moi, Pierric Cistac, Morgan Funtowicz, Joe Davison, Sam Shleifer, et al. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, 2020. 5

[48] Vikas Yadav and Steven Bethard. A survey on recent advances in named entity recognition from deep learning models. *arXiv preprint arXiv:1910.11470*, 2019. 4

[49] Evi Yulianti, Ruey-Cheng Chen, Falk Scholer, W Bruce Croft, and Mark Sanderson. Document summarization for answering non-factoid queries. *IEEE transactions on knowledge and data engineering*, 30(1):15–28, 2017. 1

[50] Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, Franziska Roesner, and Yejin Choi. Defending against neural fake news. *Neurips*, 2020. 1, 2, 3, 4, 6, 8

---

**Appendices**

**A. Article Generation**

**A.1. Additional Qualitative Results**

Additional qualitative results from various news sources are provided in Figure 7, 8, 9, 10, 11 as the supplement of our main paper.

**A.2. Zero-shot Style Transfer**

The task of our paper is automatically writing long articles and we choose news article generation as the application to validate the effectiveness of our model. In this section, we perform zero-shot style transfer to Wikipedia articles to demonstrate the capability of ENGIN on other
applications. We report perplexity results in Table 3. From the table, we see that our oracle named entities and entity-aware mechanism still can improve the performance on Wikipedia article generation, even though the data distribution between Wikipedia and news is different. For example, the GPT2 models finetuned on Visualnews get worse performance than the original GPT2 models on WikiText. However, our ENGIN models still get comparable or better results than the original GPT2 across different model size. We also present qualitative results in Figure 12, 13.

| Model Name            | $n_{params}$ | WikiText2 PPL ↓ |
|-----------------------|--------------|-----------------|
| GPT2-124M [31]        | 124M         | 26.1            |
| GPT-Neo-125M [10]     | 125M         | 24.9            |
| GPT2-124M (Finetuned) | 124M         | 33.8            |
| ENGIN-Base (NE)       | 124M         | **20.7**        |
| GPT2-355M [31]        | 355M         | 19.1            |
| GPT-Neo-1.3B [10]     | 1.3B         | **13.1**        |
| GPT2-355M (Finetuned) | 355M         | 25.2            |
| ENGIN-Medium(NE)      | 355M         | 15.4            |
| GPT2-1.5B [31]        | 1.5B         | 14.8            |
| GPT-Neo-2.7B [10]     | 2.7B         | 11.5            |
| GPT-J-6B [43]         | 6B           | **9.0**         |
| GPT2-1.5B (Finetuned) | 1.5B         | 25.9            |
| ENGIN-XL(NE)          | 1.5B         | 16.3            |

Table 3. Zero-shot results on WikiText [26]. Both finetuned GPT2 and ENGIN models are finetuned based on VisualNews [24]. The maximum length of Wikipedia articles is set to 1024.

B. Article Quality Annotation Templates

Following [37], annotators are asked to indicate a reason for whether the articles are human-written or machine-manipulated. We provide a view of the AMT worker interface in Figure 14.
Title: Daniel Agger leaves Liverpool to return to former club Brondby

Domain: www.theguardian.com
Date: 08-30-2014

Daniel Agger has rejoined Brondby for an undisclosed fee.

Human-written News Article

Liverpool have announced the sale of the defender Daniel Agger to the Danish club Brondby for an undisclosed fee. The 29-year-old Denmark international joined the Anfield club from Brondby in 2006 and went on to make more than 200 appearances for the club but had fallen down the pecking order under Brendan Rodgers.

"Liverpool have been such a big part of my life and my family’s lives for so long, that leaving is extremely difficult," Agger said. "The opportunity arose for me to return home to Brondby and at this stage of my career it felt like the right decision for me. I wouldn’t leave here to go anywhere else and that has been proven by my actions in recent seasons - I have turned down many offers to move to other Premier League and European clubs. "I would like to thank the Liverpool supporters for the incredible backing they have given me in my time here and the warmth and generosity of spirit displayed to my family. "This has been our home and somewhere we have been very happy and settled. However, more recently I have started to feel the effects of playing regularly in a league that is as physically demanding as the Premier League is, and I would not want to stay if I did not think that I was able to meet that challenge week in, week out."

ENGIN-generated News Article

The Liverpool defender Daniel Agger has left Anfield to return to his previous club Brondby. The Danish international midfielder was reported to have agreed personal terms with the club. The 29-year-old left Liverpool in 2006 following their relegation from the Premier League and has featured for the national team in Denmark’s recent seasons.

The move to Brondby was said to be a "cash - plus " deal. "We’re very pleased Daniel Agger has chosen to continue his development at Brondby," read a statement on the club website. "He’s a young man who has shown great potential in the Premier League, and we look forward to working with him again. "Brondby, who are in the Danish Superliga, have a squad of more than 200 players. The Liverpool manager Brendan Rodgers said : "As a footballer you dream of playing in the Premier League and I’m very pleased that Daniel Agger has chosen to come back to Brondby. "He’s a good defender and I’m sure he will work very hard to prove to the club that he is a good player. "We like to think of him as a very important player for his nationality. But he has a great character. You might think he’s a bit of a character but you’ll see he’s as strong a character as any of the other players here. "Ager said : "I am extremely proud to play for Brondby. "I will always consider it as one of the happiest days of my career so far. It has been a great and very memorable time, and the supporters have been fantastic. My future lies with the club, and hopefully, it will be here for a long time. "I also want to thank the Liverpool fans for their support. Without them I wouldn’t have been able to carry on fighting for this shirt, so thank you."

Figure 7. Example of human-written and ENGIN-generated news articles from Guardian.
Title: State of Britain's wildlife 'increasingly fragile'
Domain: www.bbc.com
Date: 12-08-2015

Dark green fritillary butterfly

Human-written News Article

Britain’s wildlife is in an increasingly fragile state, with animals carrying out vital jobs for farmers being lost more rapidly than others, say scientists. Insects that pollinate crops or fight pests are at risk of disappearing, putting food production in jeopardy, according to the team. The research brings together millions of wildlife records spanning 40 years. It suggests conservation efforts should focus on certain areas, they add. Dr Tom Oliver of the University of Reading, who led the research, said it was the biggest and most comprehensive report ever assembled for any country in the world. "By standardising records from an army of amateur biologists across the country, we have amassed an impressive array of data, giving us our most complete picture yet of the state of Britain’s wildlife," he told BBC News. "The picture that emerges is of an increasingly fragile system, particularly in species that do vital jobs for humans. "Unless efforts are made to reverse some of these declines, we face a future where we will be less confident that we can effectively grow our food." Benefits from nature.

The researchers looked at records of the changing fortunes of more than 4,000 types of plant and animal living in England, Wales and Scotland between 1970 and 2009. Species such as bees, dragonflies, grasshoppers, ladybirds, plants and mosses were put into groups based on the role they play in nature. Groups providing pollination and pest control benefits had undergone declines while those involved in functions such as decay or mopping up carbon emissions were more stable. Plants and animals regarded as of cultural importance to humans, such as birds, butterflies and hedgehogs, also fared badly. Prof James Bullock, of the Centre for Ecology and Hydrology in Oxfordshire, a co-researcher on the study, said conservation efforts should focus on the areas where there was strong evidence of declining fortunes. "Conservation actions, such as wildlife friendly farming, can avoid the loss of biodiversity and the resulting erosion of the pollination, pest control and other benefits we derive from nature," he said. And Dr Oliver said there were a number of measures that individuals could take to help to improve the future for wildlife in the British Isles. They include: Making gardens wildlife friendly, purchasing food grown in a sustainable way to wildlife, helping to collect data on wildlife. The study is published in the journal Nature Communications.

ENGIN-generated News Article

The state of Britain's wildlife has become increasingly fragile due to loss of habitat and changes in the climate, a study has suggested. Mass bird and butterfly losses have increased along with climate change, scientists found, which means many species are not as well equipped to cope. And while changes in food distribution, such as floods, may cause short-term problems, they can make long-term problems worse. Drought and flood events could put millions of birds and insects at risk, the scientists concluded. Monitoring of more than 4,000 species of birds, butterflies and moths across England, Wales and Scotland for 40 years concluded that the UK's biodiversity was still very good - only smaller than it was in 1975. But the biological communities in which they live were now less diverse than when these earlier surveys took place, which meant their ability to recover was less certain, they added. "We have lost several species of already endangered species," explained lead researcher Dr Tom Oliver, a naturalist at the University of Reading. "And we are moving into many of these habitats that are becoming drier and thus less suitable for them. "The results of the study were "far more alarming" than expected. "The situation looks pretty dire," said Dr James Bullock from the Centre for Ecology and Hydrology at Oxfordshire, who was not involved with the research. He told BBC News that Britain's wildlife was already extremely stressed. "Our natural environment is suffering from climate change, which is melting the ice sheets and expanding the oceans, and from human-generated pollution, so we are going to have a much more polluted environment in the future. "And the species we are losing are particularly important because when you lose species, you do so in numbers, they cease to exist in numbers." The loss of a single species in Britain alone has the potential to affect millions of other organisms. "The impact of the findings is likely to be felt most in many communities across the British Isles. "We have lost a large number of species, "Dr Oliver added. "It's going to have a big impact on the ecology of Britain. "He explained that the risk of long-term damage was unlikely to be taken lightly: "We are more concerned about short-term impacts." The researchers believe that much work needs to be done to understand how, in time, this situation might change. Research in Nature Communications suggests that climate change means there has been a sharp decline in the number of butterfly species spotted in northern England - down by a third between 1970 and 2009. Species such as the large blue have struggled for many generations as the cold weather has made it too cold to overwinter in the UK. Follow Helen on Twitter.

Figure 8. Example of human-written and ENGIN-generated news articles from BBC.
Video shows suspects robbing and attacking a Georgetown Day student.

**Human-written News Article**

A student at Georgetown Day School was robbed last month in the same area of the District where a student at another school was stabbed during a robbery attempt, and near where two other robberies also occurred last month. The student at Georgetown Day was robbed about 1:30 p.m. April 27 in the 4200 block of Davenport Street, near the private school. Three robbers approached, and began beating the victim, police said, although they did not identify him as a student. They went through his pants pocket and took his glasses, wallet and phone before fleeing on foot, police said. A spokeswoman for Georgetown Day issued a statement saying that a student there was robbed along 42nd Street in Tenleytown on April 27, and the school provided immediate medical and security support. The statement said the school has held an assembly devoted to neighborhood safety training and it has adjusted the patrols of school security officers. That robbery occurred two days after an April 25 incident in which authorities said a student at Woodrow Wilson High School was stabbed in the leg during an attempted robbery near the school. In the Wilson incident, the robber was described as a man in his 30s. No description was provided of the robbers on Davenport Street NW. Police released video Monday of three people described as "persons of interest." The video showed the victim and the robbers approaching each other on a sidewalk, with school buses lined up at a curb. Suddenly the student is knocked down and one or two of the robbers appear to go through his pockets. But the video does not appear to make possible a detailed description of the robbers. The stabbing comes nearly a week after two robberies, one of them involving a student victim, were reported on streets near Wilson and near Georgetown Day. Both occurred within about 15 minutes of each other April 19. In each instance, three people, one of whom was armed with a knife, approached female victims and demanded their cellphones and debit cards. A juvenile male has been arrested in those cases, police said.

**ENGIN-generated News Article**

A group that robbed Georgetown Day School of valuables including cash last month and a purse while it was locked up in a dormitory has also robbed a spate of Georgetown Day students, police said. The initial thefts occurred April 27 and April 27. Two men entered the school, stealing the wallets and purses of two female students, police said. A total of four men were released from custody. The school said the total was $170. The last robbery occurred about 1:30 p.m. April 27 near the store at 4200 Davenport Street. Three male suspects fled the school on foot, and a local resident engaged in an effort to help the robbers, police said. It took about 15 minutes before the local man was able to locate them. The three defendants - one in his 20s, one in his late 20s and one in his late teens - fled along Davenport Street NW and into a residential neighborhood, police said. That resident was identified as a friend of the robbers and assisted in helping apprehend them. The robbery at Georgetown Day came two days after a robbery at Woodrow Wilson High School in Tenleytown. That April 25 robbery took place near 42nd Street and Davenport Street NW, a major thoroughfare in Tenleytown. According to police, two men in their 20s robbed a woman in her 30s. The robbers fled with a purse containing cash that was in a pink leather wallet. On Monday, the Wilson robbery went unsolved for nearly a week. Staff at the school said no incidents had been reported. "We do have a staff member watching the campus. You go through the normal procedures of setting up alarms," said a Tenleytown police spokeswoman. "We were n't able to get that information from the yet. The person you are talking to is someone within security. You have to keep an eye on him." Correction: This story has been updated to reflect that the Davenport Street robbery occurred April 19, not April 27.
Title: Courts again rule against streaming upstart Aereo
Domain: www.usatoday.com
Date: 08-21-2014

Human-written News Article

A federal court will not hear Aereo's argument that the streaming media company should be allowed to operate similarly to a cable company. The Second Circuit Court of Appeals ruled Thursday that Aereo will have to take its argument to the district court, according to court documents first reported by The Washington Post. This decision continues broadcasters' winning streak against the upstart service. Launched two years ago, Aereo delivered over-the-air channels via online streaming to computers and tablets for about $8 a month and had brought the service to 11 cities. The Supreme Court ruled two months ago that Aereo was violating copyright law by not paying the networks for transmitting their signals. After that, the streaming media company voluntarily shut down and told the U.S. District Court that it wanted to be treated as the equivalent to a cable TV system and apply for a compulsory license to stream live TV broadcasts. Subsequently, the Copyright Office's general counsel said that the office did not think that Aereo would qualify, but fell short of denying Aereo's filing because the issue remained alive in the courts.

Follow Mike Snider on Twitter: @MikeSnider

ENGIN-generated News Article

The high court delivered yet another blow to Aereo in a pair of unanimous court opinions Thursday declaring the popular streaming service illegally alters the contents of customers' cable subscriptions and is guilty of violating copyright law. The Second Circuit Court of Appeals, which first ruled against Aereo two years ago, urged the justices to reject its claim that it is simply a device for consumers to access live TV without paying for it. Aereo lets consumers use a digital antenna to receive live broadcasts online and streams those broadcasts as they are being transmitted over the Internet, just like cable TV. Through those transmissions the consumer also becomes a subscriber to the over-the-air service. But even if they keep Aereo's service on, only a portion of the amount paid for cable service remains. For example, for $16.95 per month Aereo customers receive nearly all the TV shows they request, regardless of what shows they watch. For about $8 each the consumer loses the signals they might already have over the Internet. Thus the company is violating copyright law by redistributing the service users already pay for without paying for the service they are receiving from cable operators. "The Court finds that Aereo's business model violates this section of the Copyright Act," 11 judges wrote in the majority opinion. The Washington Post, which first reported on the decision, called it "a blow to digital media and to consumers." "This unanimous decision means a lot," Aereo chief executive Mike Snider said in a statement. "Consumers no longer have to pay to receive the traditional way they watch TV. They now have the option to pay only for a service that delivers those channels, all for free." Aereo has petitioned the court to change the district court's ruling to the full appeals court, which is likely to do so. The Supreme Court upheld the same ruling from two months ago. Aereo said it will appeal to the U.S. District Court for the District of Columbia. Experts tell the Post that its previous case shows that the Copyright Office's determination to give consumers access to streaming services without paying retailed companies is likely to be reversed by the appeals court.

Follow @jswartz on Twitter

Figure 10. Example of human-written and ENGIN-generated news articles from USA Today.
James F. Holland, a founding father of chemotherapy who helped pioneer a lifesaving drug treatment for pediatric leukemia patients, died on Thursday at his home in Scarsdale, N.Y. He was 92.

The cause was respiratory failure, his son Steven said.

Dr. Holland and his medical collaborators in the 1950s were scorned by some colleagues as research "cowboys," as he put it, because they audaciously tackled what was considered an incurable disease and tried to treat it with several chemicals simultaneously, instead of sequentially.

When their research began, fewer than one in three children who were found to have acute lymphoblastic leukemia lived as long as a year. Today, as many as nine in 10 survive the disease, in which the bone marrow makes too many immature white blood cells.

Another clinical trial that Dr. Holland directed in the 1970s, to contain acute myeloid leukemia, a somewhat similar malfunction in blood cell production, resulted in what became the standard treatment.

The cause was a widespread myeloid leukemia subtype, a cancer of the blood cells in bone marrow that occurs in fewer than one in three patients.

Mr. Holland was one of the few oncologists to propose, in the 1950s, the chemical treatment known as prednisolone – hence the name. He was also among the first to suggest (though not actually carry out) what became known as precancer therapy: turning over nonmedical patients to their regular doctors, while supplementing their therapies with medications to kill cancer cells. The mere suggestion of precancer therapy, it seemed to some, would have rendered it toxic.

At the time, though, Mr. Holland thought it should not. He and his colleagues had been working for as long as a year on drugs to prevent acute lymphoblastic leukemia in patients with advanced disease, in which cells on the surface of the blood can proliferate out of control after being overexposed by chemotherapy. Doctors usually did this only after the patient's health deteriorated. Today, many hospitals will not perform precancer therapy, either.

But in the 1970s, he and his colleagues were regarded as "research cowboys" by their colleagues. Known for treating as many as nine of 10 cancer cases, they had been derided even by their own specialty, nuclear medicine, for treating these patients when "the science does not justify it," Dr. Steven Holland, his brother and his only sibling, said.
Robert Boulter

Robert Boulter is an English film, television and theatre actor. He had a guest @-@ starring role on the television series The Bill in 2000. This was followed by a starring role in the play Herons written by Simon Stephens, which was performed in 2001 at the Royal Court Theatre. He had a guest role in the television series Judge John Deed in 2002. In 2004 Boulter landed a role as \"Craig\" in the episode \"Teddy\'s Story\" of the television series The Long Firm; he starred alongside actors Mark Strong and Derek Jacobi. He was cast in the 2005 theatre productions of the Philip Ridley play Mercury Fur, which was performed at the Drum Theatre in Plymouth and the Menier Chocolate Factory in London. He was directed by John Tiffany and starred alongside Ben Whishaw, Shane Zaza, Harry Kent, Fraser Ayres, Sophie Stanton and Dominic Hall. In 2006, Boulter starred alongside Whishaw in the play Citizenship written by Mark Ravenhill. He appeared on a 2006 episode of the television series, Doctors, followed by a role in the 2007 theatre production of How to Curse directed by Josie Rourke. How to Curse was performed at Bush Theatre in the London Borough of Hammersmith and Fulham. Boulter starred in two films in 2008, Daylight Robbery by filmmaker Paris Leonti, and Donkey Punch directed by Olly Blackburn. In May 2008, Boulter made a guest appearance on a two @-@ part episode arc of the television series Waking the Dead, followed by an appearance on the television series Survivors in November 2008. He had a recurring role in ten episodes of the television series Casualty in 2010, as \"Kieron Fletcher\". Boulter starred in the 2011 film Mercenaries directed by Paris Leonti. In 2000 Boulter had a guest @-@ starring role on the television series The Bill; he portrayed \"Scott Parry\" in the episode, \"In Safe Hands\". Boulter starred as \"Scott\" in the play Herons written by Simon Stephens, which was performed in 2001 at the Royal Court Theatre. A review of Boulter's performance in The Independent on Sunday described him as \"horribly menacing\" in the role, and he received critical reviews in The Herald, and Evening Standard. He appeared in the television series Judge John Deed in 2002 as \"Addem Armitage\" in the episode \"Political Expediency\", and had a role as a different character \"Toby Steele\" on The Bill. He had a recurring role in 2003 on two episodes of The Bill, as character \"Connor Price\". In 2004 Boulter landed a role as \"Craig\" in the episode \"Teddy\'s Story\" of the television series The Long Firm; he starred alongside actors Mark Strong and Derek Jacobi. Boulter starred as \"Darren\", in the 2005 theatre productions of the Philip Ridley play Mercury Fur.

Figure 12. Zero-shot style transfer to Wikipedia articles (from WikiText dataset [26]). We generate articles conditioned on both the title Robert Boulter, and the first 50 tokens highlighted by light yellow. The articles are cut fit the figure size.
The 1933 Treasure Coast hurricane was the second most intense tropical cyclone to strike the United States during the active 1933 Atlantic hurricane season. The eleventh tropical storm, fifth hurricane, and the third major hurricane of the season, it formed east of the Leeward Islands on August 31. The tropical storm moved rapidly west northwestward, steadily intensifying to a hurricane. It acquired peak winds of 140 miles per hour (225 km/h) and passed over portions of the Bahamas on September 3, including Eleuthera and Harbour Island, causing severe damage to crops, buildings, and infrastructure. Winds over 100 mph (161 km/h) affected many islands in its path, especially those that encountered its center, and many wharves were ruined. Subsequently, it weakened and made landfall at Jupiter, Florida, early on September 4 with winds of 125 mph (201 km/h). The hurricane moved across the state, passing near Tampa before moving into Georgia and dissipating. In Florida, the strong winds of the cyclone blew buildings off their foundations, and numerous trees were prostrated in citrus groves. The Treasure Coast region received the most extensive destruction, and Stuart, Jupiter, and Fort Pierce were heavily damaged. Inland, the cyclone weakened rapidly but produced prodigious amounts of rain, causing a dam to collapse near Tampa. The storm caused $3 million in damage ($1933 USD) after damaging or destroying 6,848 homes. Unusually, the storm hit Florida less than 24 hours before another major hurricane bearing 125 mph (201 km/h) winds struck South Texas; never have two major hurricanes hit the United States in such close succession. The origins of the hurricane were from a tropical wave that possibly spawned a tropical depression on August 27, although there was minimal data over the next few days as it tracked to the west northwest. On August 31, a nearby ship reported gale force winds, which indicated that a tropical storm had developed to the east northeast of the Lesser Antilles. Based on continuity, it is estimated the storm attained hurricane status later that day. Moving quickly to the west northwest, the storm passed north of the Lesser Antilles and Puerto Rico. Early on September 2, a ship called the Gulfwing reported a barometric pressure of 978 mbar (28.88 inHg), which confirmed that the storm attained hurricane status. After passing north of the Turks and Caicos islands, the hurricane struck Eleuthera and Harbour Island in the Bahamas on September 3, the latter at 1100 UTC. A station on the latter island reported a pressure of 27.90 inHg (945 mb) during the 30 minute passage of the eye.

1933 Treasure Coast hurricane

Human-written Wikipedia

The 1933 Treasure Coast hurricane was the second most intense tropical cyclone to strike the United States during the active 1933 Atlantic hurricane season. The eleventh tropical storm, fifth hurricane, and the third major hurricane of the season, it formed east of the Leeward Islands on August 31. The tropical storm moved rapidly west northwestward, steadily intensifying to a hurricane. It acquired peak winds of 140 miles per hour (225 km/h) and passed over portions of the Bahamas on September 3, including Eleuthera and Harbour Island, causing severe damage to crops, buildings, and infrastructure. Winds over 100 mph (161 km/h) affected many islands in its path, especially those that encountered its center, and many wharves were ruined. Subsequently, it weakened and made landfall at Jupiter, Florida, early on September 4 with winds of 125 mph (201 km/h). The hurricane moved across the state, passing near Tampa before moving into Georgia and dissipating. In Florida, the strong winds of the cyclone blew buildings off their foundations, and numerous trees were prostrated in citrus groves. The Treasure Coast region received the most extensive destruction, and Stuart, Jupiter, and Fort Pierce were heavily damaged. Inland, the cyclone weakened rapidly but produced prodigious amounts of rain, causing a dam to collapse near Tampa. The storm caused $3 million in damage ($1933 USD) after damaging or destroying 6,848 homes. Unusually, the storm hit Florida less than 24 hours before another major hurricane bearing 125 mph (201 km/h) winds struck South Texas; never have two major hurricanes hit the United States in such close succession. The origins of the hurricane were from a tropical wave that possibly spawned a tropical depression on August 27, although there was minimal data over the next few days as it tracked to the west northwest. On August 31, a nearby ship reported gale force winds, which indicated that a tropical storm had developed to the east northeast of the Lesser Antilles. Based on continuity, it is estimated the storm attained hurricane status later that day. Moving quickly to the west northwest, the storm passed north of the Lesser Antilles and Puerto Rico. Early on September 2, a ship called the Gulfwing reported a barometric pressure of 978 mbar (28.88 inHg), which confirmed that the storm attained hurricane status. After passing north of the Turks and Caicos islands, the hurricane struck Eleuthera and Harbour Island in the Bahamas on September 3, the latter at 1100 UTC. A station on the latter island reported a pressure of 27.90 inHg (945 mb) during the 30 minute passage of the eye.

ENGIN-generated Wikipedia

The 1933 Treasure Coast hurricane was the second most intense tropical cyclone to strike the United States during the active 1933 Atlantic hurricane season. The eleventh tropical storm, fifth hurricane. A Category 4 cyclone with winds of 100 mph generated winds of 161 km per hour and a water temperature of 49 degrees. The storm killed 6 people, flooded an area of 848 sq km, and caused $3 million in damage. Although it missed the Florida coast, the system swept across the rest of the United States less than 24 hours. The heat from the system caused widespread fires and continued to bring heavy rain and wind throughout the south and central regions. In south Florida alone, the fires killed two men and destroyed 98 homes in the Lesser Antilles and southwest Florida. The Turks and Caicos islands were particularly badly hit because of a storm surge that produced high seas and flooding, especially along the coast from Tampa, Georgia, to Puerto Rico. The Turks and Caicos islands experienced over 125 mph winds, winds of 125 mph per hour, and only 1 cm to 2 inches of rain in the 30 minute interval starting around 1400 UTC. The Turks and Caicos islands also experienced an over 140 mph wind shear at 5875 kph. In south Georgia, home to the Simpson and Penally counties, the worst of the damage was felt in the Savannah area, where 800 homes were damaged or destroyed and well over 1000 had to be demolished. The most intense tropical storm to strike the United States during the 1933 Atlantic hurricane season occurred when Tropical Depression 6 formed over the Bahamas during the winter of 1913. The storm resulted in catastrophic loss of life and destruction. As of 24 km west of the Bahamas, the lowest pressure was 3.21 mb, and the storm had maximum sustained winds of 200 km/h, with gusts to over 200 km/h. In south Florida, the intense storm produced winds of 100 mph over southwest Florida and a south-western coast generally between the edges of the Low Range and the extreme southeast of the storms. In western Cuba, the storms produced winds up to what the Weather Bureau described as ‘about 65 mph’ in some spots, and all tropical storms at Category 4, 5 and 7, respectively, were downgraded to a tropical storm or depression. Texas though was hit by Hurricane Norbert in early October 1913. At the time, the Weather Bureau reported that the storm produced winds of 800 - 900 km/h, and a storm tide of 848 m. The storm passed over northeast Texas between midnight and dawn, and was the first major tropical cyclone to impact the United States during the winter of 1913. Norbert resulted in 848 lives being lost and $98 m in damages, amongst other catastrophic damage, as well as numerous fatalities.

Figure 13. Wikipedia articles about 1993 Treasure Coast hurricane.
Instructions: News Articles Evaluation

Hello, we are trying to determine how susceptible people are to machine-generated fake news.

In this study, you are asked to discriminate between human and machine-generated news articles. You will be assigned 5 article samples. Each article sample contains the headline, article body and image/caption pairs. The images and captions are located after the article body where each caption is situated below its corresponding image.

You should spend no more than 1 to 1.5 minutes on each article.

Please be sure to click the submit button for each article.

Please note that we re-rendered all the article samples. As a result, the primitive display is NOT an indicator of whether the article is human or machine generated.

Figure 14. The interface used by AMT workers in our article quality annotation experiment.