Predicting guilt judgments from crime stories

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Abstract

[ek: update abstract wrt new framing] News has become a central part of our lives and with it our assessments and reproductions of these stories. However, the way in which humans assess guilt on the basis of such crime stories is unclear. If neural networks can learn to predict guilt judgments from a news story, they can help us form hypotheses about relevant features for human guilt predictions. However, whether neural networks can even learn to predict guilt judgments from a given news story is still an open question. In this paper, we will present a bidirectional LSTM with self-attention that makes a promising first step to predict guilt judgments. On the basis of attention visualizations, we argue that the model learns meaningful patterns from the data that guides its prediction.

1 Introduction

Deep learning models are increasingly applied to language tasks not only to develop technologies but also to derive new insights into language use. These more scientific applications raise the question of whether the models are processing data in a motivated way; their "black box" nature is often an obstacle to answering this question (Alishahi et al., 2019). Recently, attention mechanisms, which capture the strength of association beween components of these networks (Bahdanau et al., 2015; Luong et al., 2015), have not only improved performance, but also increased interpretability, potentially opening the door to new linguistic applications of these models (cf. (**?**)).

In this paper, we apply neural networks with attention to a task that has both linguistic and societal import: predicting whether the reader of a short narrative crime report will conclude that the main subject is guilty or innocent. Our networks achieve strong performance on this task, as defined by the dataset of Kreiss et al. (2019), which leads us to explore their learned parameters by inspecting how they predictions for new, carefully controlled examples. Our central finding is that, where the evidence is weak, the networks make robust use of markers of certainty and uncertainty, as indicated by the large attention weights for such terms. In contrast, where the evidence is strong, these markers contribute less (have smaller attention weights). To the extent that human adopt similar reading strategies, this can inform how the news is reported, in that it gives us insights into the contribution of words like *allegedly* and *possibly* in shaping readers' construal of newspaper articles.

2 Related work

2.1 Predicting guilt

The challenge of predicting guilt judgments from text sources has not yet received a lot of attention. However, Fausey and Boroditsky show that using agentive language increases blame and financial liability judgments people make. Furthermore, they find that this effect is robust against other evidence for example through short video material of the incident. Their results suggest that even subtle linguistic changes in crime reports can shape people's judgments of the events. More recent work has focused on predicting guilt verdicts from the Supreme Courts in the Philippines (Virtucio et al., 2018) and Thailand (Kowsrihawat et al., 2018) on the basis of facts presented and law texts. Kowsrihawat et al. argue for a recurrent neural network with attention to make these predictions and achieves [ek: accuracy]. Note that this work is not concerned with the linguistic basis of subjective moral guilt judgments, but Court guilt verdicts on the basis of a given law text.

2.2 Interpretation of hedges

In the literature, researchers have categorized and labeled (un)certainty markers in numerous ways, e.g., (Lakoff, 1972; Prince et al., 1982; Brown et al., 1987). For a summary we refer readers to consult (Fraser, 2010). For this work, we use "hedge" as an umbrella term for all subclasses of uncertainty markers. In this vein, for our purposes, "hedge" refers to any marker that introduces uncertainty "within the propositional content" (e.g., His feet were **sort of** blue.), or "in the relationship between the propositional content and the speaker" (e.g., **I think** his feet were blue.).

But how do people understand hedges? Corpus studies as well as empirical studies show that hedges can have an effect on the perception of the speaker and the proposition itself (Erickson et al., 1978; Durik et al., 2008; Bonnefon and Villejoubert, 2006; Rubin, 2007; Jensen, 2008; Ferson et al., 2015). These studies have shown that hedges affect people's trustworthiness in differing ways, for example an increase in the number of hedges decreases the credibility of witness reports (Erickson et al., 1978) but at the same time increases the trustworthiness of journalists and scientists (Jensen, 2008). Additionally, the interpretation of hedges is highly context dependent (Bonnefon and Villejoubert, 2006; Ferson et al., 2015), has individual variation (Rubin, 2007; Ferson et al., 2015), and is sensitive to the positioning of the hedges (Durik et al., 2008).

2.3 Gaining linguistic insights through neural networks

3 Dataset

For training and testing the model, we use the Annotated Iterated Narration Corpus (AINC) collected by (Kreiss et al., 2019). The corpus was created for investigations on how news stories change when they are propagated from one person to another. First the authors created five stories of approximately 850 words, which are called the *seed* stories. All of them report a crime and an arrest of one or more suspects. Each of these five seed stories exists in a weak and a strong evidence condition. The stories are identical up to the last phrase, which then either raises doubts about the arrest or emphasizes its validity. For example, if a suspect was arrested on the basis of camera footage, this footage was described as being of "very poor quality" in the weak evidence condition and "very high quality" in the strong evidence condition. Each story was given to a participant who was asked to read and afterwards reproduce it. The reproduced story was then given to the next participant who again reproduced it. This pattern was repeated for 5 generations of participants. The data collection therefore followed the transmission-chain paradigm, introduced by (Bartlett, 1932). Following this schema, each story and condition was reproduced in 5 chains over 5 generations, resulting in 250 reproductions, and therefore 260 stories overall (see Figure 1).

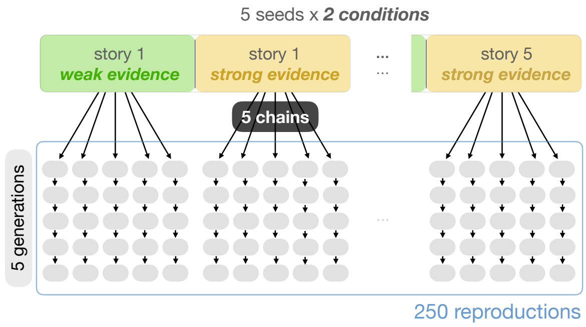

Figure 1: Corpus collection schema as presented in (Kreiss et al., 2019).

After the corpus collection, Kreiss et al. annotated the corpus with human judgments. The questions were primarily related to different aspects of guilt perception but also, for example, perceived subjectivity of the story writing. Participants were recruited on Amazon Mechanical Turk and indicated their response on a continuous slider, here underlyingly coded as ranging from 0 to 1. Most interestingly for this project, they asked "How likely is it that the suspect is / the suspects in the crime are guilty?" Each story received approximately 20 ratings, ranging from 0 to 1. For the purposes of this work, we consider the mean rating for each story as its guilt judgment label. The labels of each story are shown in Figure 2. In contrast to the raw ratings, the means only range from 0.27 to 0.92.

In summary, the AINC is a corpus of reproduced news stories, annotated by human guilt judgments. Since the stories originated from only 5 unique stories (each in 2 conditions), a lot of information is shared between single data points. Despite this similarity, the range of guilt judgments is still high, alluding to subtle differences that trigger this variance. We now turn to the question of whether a deep learning model can learn

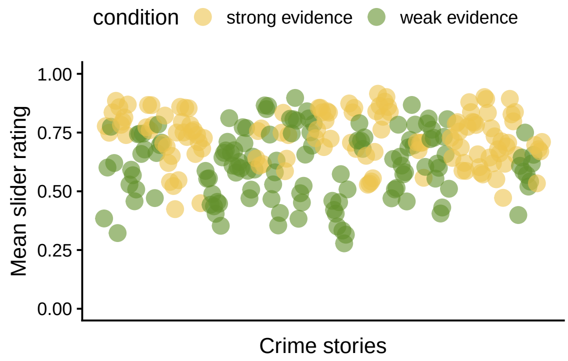

Figure 2: A point represents the mean subject guilt rating for a story in the corpus. They are color-coded with respect to their condition.

to predict the assessments of guilt the corpus provides.

4 Model

Our starting point is a model first proposed by Lin et al., which is fundementally a bidirectional LSTM with attention mechanisms applied to its outputs. We chose this model primarily because its attention mechanisms seem especially promising for introspection. The overall architecture is summarized in Figure 3.

We made two major adjustments to the model proposed by Lin et al.. First, we replaced the GloVe word embeddings (Pennington et al., 2014) by BERT representations (Devlin et al., 2019). Whereas GloVe provides a single embedding for each word, with no sensitivity to the context in which it occurs, BERT representations vary by syntactic context. Devlin et al. report that using these embeddings boosts performance in all of the 11 natural language tasks it was trained on compared to previous systems, and we saw comparable improvements when we switched from GloVe to BERT. To access pretrained BERT parameters, we used the Hugging Face toolkit.[1]

Second, we simplified Lin et al.'s attention module. The inputs to this module are the n hidden states of the LSTM, which we store as a matrix $H \in \mathbb{R}^{n\times 400}$. In the attention module, we apply a dense layer with parameters $W_{a_1} \in \mathbb{R}^{400\times 50}$ and a $\tanh$ activation function, resulting in matrix of 50-dimensional representations $A_1 \in \mathbb{R}^{n\times 50}$:

$$A_1 = \tanh(HW_{a_1})$$

[1] https://github.com/huggingface/pytorch-transformers

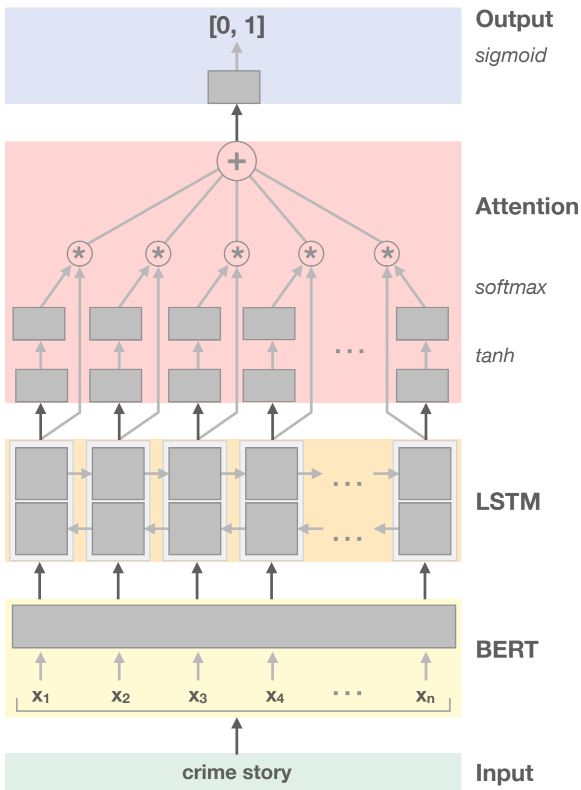

Figure 3: Model architecture. The network receives a crime story as its input. We rely on BERT to tokenize this text in a way that aligns with its token embedding (Wu et al., 2016). The resulting token sequences is processed by BERT to produce a sequence of contextual representations. These are the input to a bidirectional LSTM layer, which fine-tunes the BERT representations for our task. This sequence of vectors is transformed into a vector of weights, which are used to create a weighted sum of those vectors that serves as the input to the regression layer at the very top, which learns from scalar guilt judgments.

The matrix A_1 is further compressed to the attention weight vector $\mathbf{a_w}$ of size 50×1, with a softmax applied so that the weights sum to 1:

$$\mathbf{a_w} = \mathrm{softmax}(A_1 \mathbf{w_{aw}})$$

Now we take the dot product of the LSTM hidden state matrix H and the just obtained vector a_w to obtain the attention output vector $\mathbf{a}_{\text{out}}$ of size 400.

$$\mathbf{a}_{\text{out}} = a_w^\top H$$

This is the output of the attention module. Intuitively, the attention weights capture the relative importance of each token with regard to the final prediction, and $\mathbf{a}_{\text{out}}$ synthesizes all of these weighted contributions into a single vector.

Finally, the logistic regression module is represented by a blue box in Figure 3. For a prediction, $\mathbf{a}_{\text{out}}$ is linearly transformed into a single number $p = \mathrm{sigmoid}(\mathbf{a}_{\text{out}})$. The sigmoid function ensures that the prediction lies between 0 and 1, just like the restriction on the guilt judgments it is trained on.

Overall, the model has 111,054,742 trainable parameters. This sounds mismatched with our very small dataset, but only 0.02% of these parameters are in the attention and output modules and 1.40% are in the LSTM module. The rest of the parameters (98.59%) are the pretrained weights in the BERT word embedding module.

In summary, the model receives a crime story as an input. BERT word embeddings for the story feed into a bidirectional LSTM. The attention module computes the weighted sum over the LSTM's hidden states. The resulting attention vector is fed through a linear layer and a Sigmoid function to ensure that the prediction lies between 0 and 1.

4.1 Training

To begin with, we randomly held back 26 stories (from the 260 stories in total) as the final test set. This helps to assess the model performance on a set of stories which has never been evaluated in the process of model development. The remaining 234 stories were then for used for model training and validation, which was done using 10-fold cross validation. The cross-validation results inform us about the model variation given various training/validation splits. For example, it is quite likely that given the small size of the dataset, this variation could be quite high. Note that, each fold had either 23 or 24 stories in it, each of which was associated with a guilt rating that functioned as the target label. Recall that this guilt rating is the mean subject guilt rating obtained from the previously described data collection and annotation.

For training, the model uses mean squared error (MSE) as the loss function, stochastic gradient descent as the optimizer and a learning rate of 0.1. The whole model was implemented using pytorch (Paszke et al., 2017). It was trained for 30 epochs, for each of the 10 training/dev-test configurations in the cross-validation.

5 Experiment

This work investigates whether a bidirectional LSTM with self-attention (as described in Section **??**) can predict human guilt judgments from news stories. In each step of the 10-fold cross-validation, the model was trained on 206/207 stories and 23/24 were held out for dev-testing. Each story has an associated suspect guilt rating, which is the mean rating obtained from human judgments. This value functions as the target label.

Since the target labels only range between 0.27 and 0.92, one potential problem might be that the model only learns to predict the overall mean of the labels in the training data. We would also expect this outcome if the model does not find any features that it can take as predictors for guilt ratings. This is why, the baseline model to test the dev-test data on will simply predict the mean of the training data labels. If the our model outperforms this baseline, we will consider it worthy of further investigations.

Both model performances will be evaluated on the mean-squared error (MSE) of their prediction to the target label on the cross-validation test set.

5.1 Results

Figure 4 shows the mean squared error (MSE) loss for each training epoch. Firstly, the training loss (in blue) is approaching a loss of 0 toward the end of the training in all cross-validation configurations. Thus the amount of training epochs seems to be sufficient. Crucially, the dev-testing loss (in orange) is overall lower after the last training epoch than the baseline (in yellow). Therefore, the model obtains information from the dataset that it can use to improve its predictions. However, there is also a high amount of variation between the different

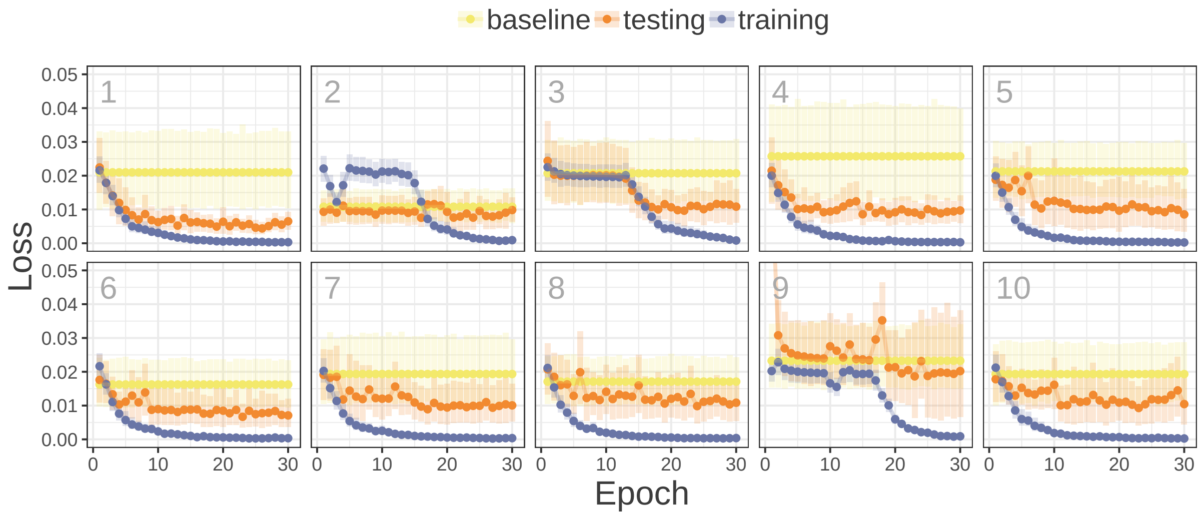

Figure 4: Loss (mean squared error) over epochs (x axis), faceted over cross-validation configurations. The performance of the model on the training set (in blue) approaches zero. The performance of the model on the dev-test set (in orange) generally outperforms the baseline (in yellow).

cross-validation steps. The mean of the training labels alone (i.e., the baseline) only has a very small loss on cross-validation configuration 2 and the trained model can barely beat it. This is in clear contrast to cross-validation step 4, where the baseline model loss is very high on the dev-test data and the trained model can easily surpass it. Those two cases exemplify the high variation that comes with the different splits of training and dev-testing data[2].

But looking at the MSE loss alone is not on its own sufficiently informative to assess how well the model actually learns to predict the underlying distribution. Figure 5 shows the correlation between the actual target label (on the x axis) and the model prediction (on the y axis) for cross-validation step 0. Before training, the training and dev-testing data has a high variance around the perfect correlation line ($r = 1$). The model only predicts values between 0.48 and 0.79. However, the underlying labels range from 0.31 to 0.92. Even though the Pearson correlation still predicts a rather high correlation on the testing set ($r = 0.65$), the mean squared error is comparably high with 0.022.

Already qualitatively, the model predictions after training (Figure 5) seem far more informative. Now the model predictions have approximately the same range as the target labels (between 0.33

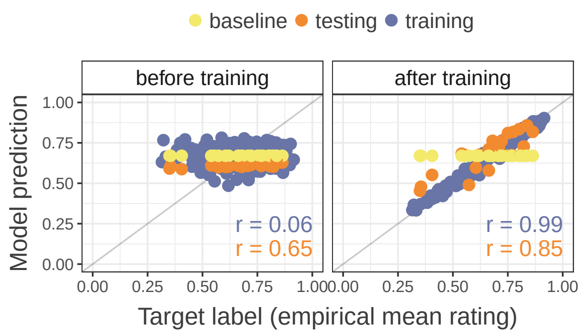

Figure 5: Correlation between target label (x axis) vs. model prediction (y axis) before and after training.

and 0.91). The Pearson correlation itself is now 0.85, and the mean squared error reduced to 0.007.

Since the baseline model does not learn over training epochs, its predictions stay the same.

Qualitatively, these plots appear very similar throughout all cross-validation configurations and can be compared in Figure 9 and 10 in the Appendix. However, quantitatively the correlation on the dev-test set changes. Those differences are mainly driven by outliers.

Overall, the mean correlation between the model prediction and the human judgment on the testing set across all cross-validation steps is 0.68. When we collapse over all cross-validation folds and examine the loss after training, the difference in loss between the model predictions and baseline is significant ($p < 0.0001$).

As a final performance evaluation, we can

[2]However, I cannot exclude that also the random parameter initialization plays a relevant role here. But at least the differences in the baseline are definitely caused by the different splits.

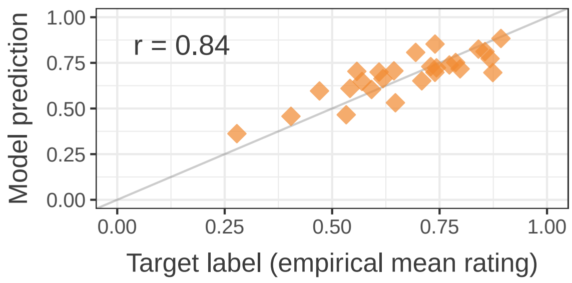

Figure 6: Testing label (x axis) vs. model prediction (y axis) after training on the held out test set (26 data points) using the parameter settings obtained after the 30th epoch from the first cross-validation. Pearson correlation of 84%.

examine the target-prediction correlation on the held-out test set (see Figure 6). For predictions on the test set, we used the final model weights obtained by the first cross-validation configuration. This setup was chosen, because of the low dev-testing loss and the high correlation of the dev-test set with the target labels[3].

The Pearson correlation on the held-out test set is still 0.84 and almost identical with the performance on the dev-test set. This fairly high correlation and the fact that the high correlation reproduces with the held-out testing data indicates that the model learns something meaningful that can generalize well.

6 Model analysis

We have seen that the proposed model can predict human guilt judgments when given a crime story. However the question remains whether there are patterns that underlie these predictions and whether we can interpret them. This is especially necessary, if we want the model to inform hypotheses about the processes that possibly underlie human judgments.

6.1 Visualization

First, we need to investigate whether the model seems to pick up on patterns that are meaningful and possibly even interpretable for us.

In the original introduction of the attention mechanism, Vaswani et al. suggested that a visualization of the attention weights can inform us about what affects the network's prediction. We follow this approach to look for first indications of a meaningful representation in the $\mathbf{w_{aw}}$ attention weight vector described in Section **??**. Since the softmax forces the sum of the weights to be 1, we cannot interpret the weights on their own for each word or across stories. Instead, the relevance lies in the differences between words and phrases within each story and pattern similarities between stories.

To investigate what might affect model predictions, we ran the model again on the final test data (as described in Section 5.1). Figure 7 displays three of these stories with their attention weight distribution.

The model seems to focus on phrases that explicitly describe uncertainty about the evidence (see Figure 7C). If present, they usually outweigh the rest of the story. This suggests that if there is an explicit claim that affects the evidence of the suspect's guilt, it is considered as the most important source to inform guilt judgment.

Additionally, peaks occur on words and phrases which communicate turning points in a story, such as "however", "but", "even though" and "it turns out". This can be seen in all three stories in Figure 7. Those phrases could be relevant because they usually indicate a contrast to a prior narrative. Since those markers mostly follow reports of arrests, they might be strongly correlated with objections to those arrests which would in turn influence guilt perceptions.

Figure 7B shows a case where the model seems to find a simple declarative ("two boys destroyed") to be relevant for the final prediction. This is especially interesting, since declaratives on their own do not generally communicate guilt-related information. However, they are very important for guilt judgments because they do not allow any uncertainty about the association between crime and suspect.

In summary, the visualization of the attention weights contribute further evidence that the model learns meaningful patterns in the data.

6.2 Qualitative analysis

The model visualization provides evidence for the claim that the model picks up on meaningful patterns in the corpus. This allows us to use the model to inform new hypotheses.

But does the model make reasonable predictions on newly constructed data points? The original corpus started out with five different crime sto-

[3]This was the only evaluation that was performed on this held-out test set.

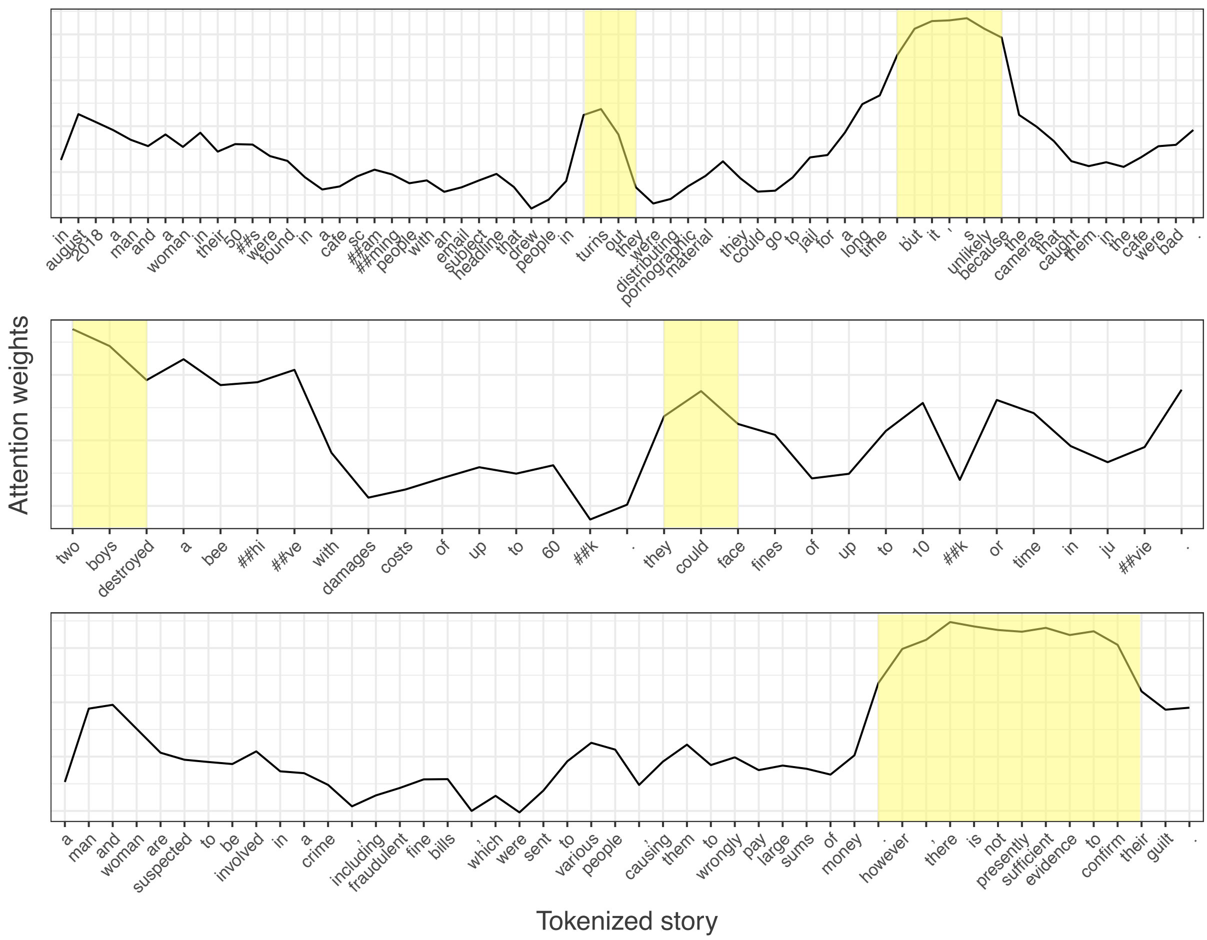

Figure 7: Visualization of the attention weights (y axis) for a tokenized story (x axis) from the test set. Because we took the softmax over the attention weights, the scale of the y axis is irrelevant. Interesting aspects are marked in yellow.

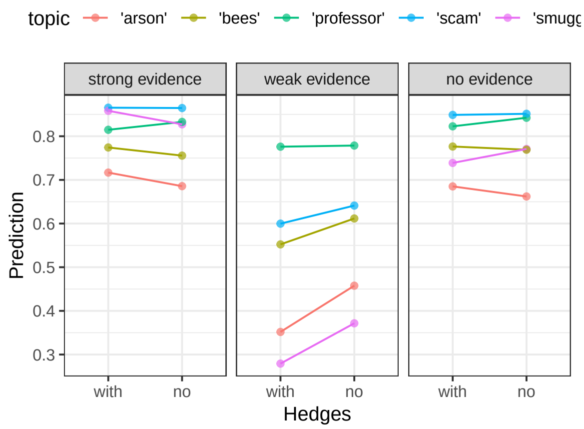

Figure 8: Model predictions on the relationship between uncertainty markers and evidence statements. [ek: fix caption and make figure more readable]

ries. Each of these stories occurred in two conditions – one suggesting that the evidence that led to the arrest was weak, and the other that the evidence provided a strong case. Additionally, the stories were filled with uncertainty markers such as "allegedly" or "(un)likely". The corpus cannot inform us about the relationship between those uncertainty markers and the evidential manipulation. What happens if we ask the model to predict a guilt judgment for each of the original stories without those uncertainty markers/hedges?

To investigate how hedging influences model predictions, we rewrote those 10 original stories into versions without any uncertainty markers. Note that they remained as close to the original as possible, while still remaining grammatical.

Figure 8 shows the results of this analysis. The results suggest that uncertainty markers have different effects on guilt prediction in the two evidence conditions. When the evidence is strong, removing all uncertainty markers does not affect the guilt judgments. However when the evidence is weak, removing those hedges increases the guilt judgment.

This allows for an intuitive interpretation. When evidence already overwhelmingly speaks for the suspect's guilt, it outweighs the hedges. However if the evidence is questionable, other sources of uncertainty are considered to inform a final judgment.

Notably if the evidence manipulation is excluded, the model predicts guilt judgments in the range of the strong evidence condition. In other words, the model predicts that a reassurance that the arrest is justified does not change the guilt judgments. However, formulating explicitly that there are reasons to question the arrest, causes the guilt assessments to drop. When we remove the hedges again, we cannot see a common structure to the change in ratings (possibly more similar to the strong evidence ratings though).

6.3 Conclusion

In this section we showed that our attention module provides intuitive insight into the model workings. Furthermore, the model makes interesting predictions on new data.[ek: ...]

7 Discussion

The results show that when given a news story, a bidirectional LSTM with self-attention can already capture something essential about human guilt judgments. Especially considering the limited amount of data (only 236 data points in the training set), the model can already extract meaningful features for guilt judgment predictions.

So far, the model has not been subjected to hyperparameter tuning. It is likely that this will further boost the model's performance. Furthermore, it is plausible that training and testing the model on the guilt ratings directly instead of their means can further increase the performance, since only showing the means hides a vast amount of information about the underlying distribution of ratings which can be very meaningful. For example, a news story where participants highly vary in their judgments should influence the model predictions less than a story with low variance.

The introduced model is a promising first step to develop a better understanding of human guilt judgments. I am confident that in the future models like these can be used to inform hypotheses about what humans consider for their assessment. This can in turn inform us about how different reporting on a news story will influence these assessments.

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8 Appendices

Figure 9: Testing label (x axis) vs. model prediction (y axis) before training; faceted over cross-validation configurations.

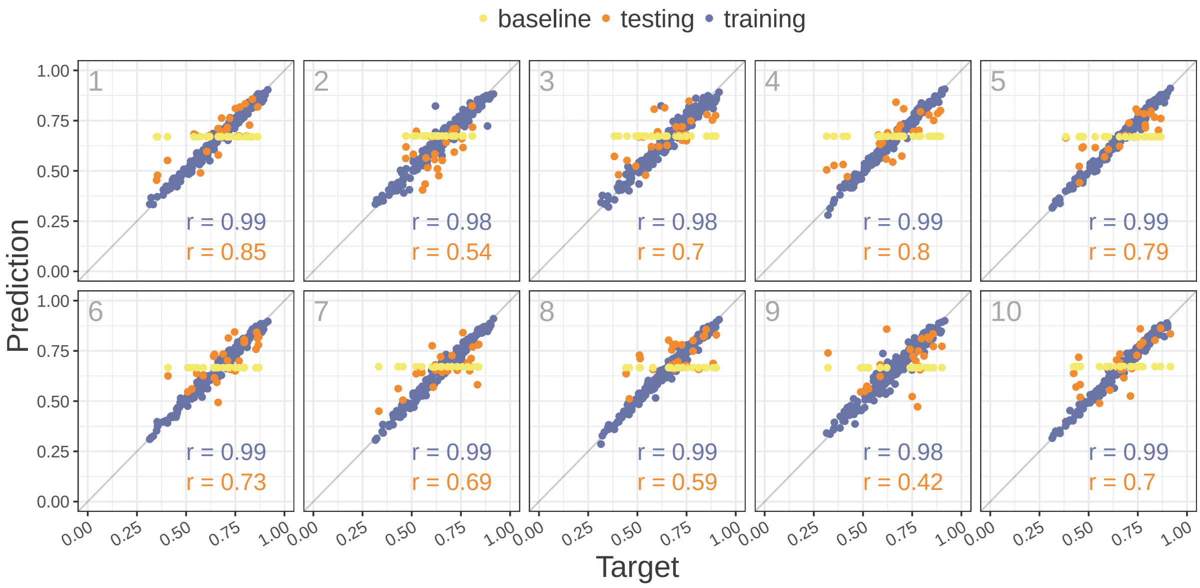

Figure 10: Testing label (x axis) vs. model prediction (y axis) after training; faceted over cross-validation configurations.