Factuality Checking in News Headlines with Eye Tracking

Hansen, Christian; Hansen, Casper; Simonsen, Jakob Grue; Larsen, Birger; Alstrup, Stephen; Lioma, Christina

Published in:
SIGIR 2020 - Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval

DOI:
10.1145/3397271.3401221

Publication date:
2020

Document version
Publisher's PDF, also known as Version of record

Document license:
Other

Citation for published version (APA):
Hansen, C., Hansen, C., Simonsen, J. G., Larsen, B., Alstrup, S., & Lioma, C. (2020). Factuality Checking in News Headlines with Eye Tracking. In SIGIR 2020 - Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 2013-2016). Association for Computing Machinery. https://doi.org/10.1145/3397271.3401221
Factuality Checking in News Headlines with Eye Tracking

Christian Hansen
University of Copenhagen
chrh@di.ku.dk

Casper Hansen
University of Copenhagen
c.hansen@di.ku.dk

Jakob Grue Simonsen
University of Copenhagen
simonsen@di.ku.dk

Birger Larsen
Aalborg University
birger@hum.aau.dk

Stephen Alstrup
University of Copenhagen
s.alstrup@di.ku.dk

Christina Lioma
University of Copenhagen
c.lioma@di.ku.dk

ABSTRACT

We study whether it is possible to infer if a news headline is true or false using only the movement of the human eyes when reading news headlines. Our study with 55 participants who are eye-tracked when reading 108 news headlines (72 true, 36 false) shows that false headlines receive statistically significantly less visual attention than true headlines. We further build an ensemble learner that predicts news headline factuality using only eye-tracking measurements. Our model yields a mean AUC of 0.688 and is better at detecting false than true headlines. Through a model analysis, we find that eye-tracking 25 users when reading 3-6 headlines is sufficient for our ensemble learner.

KEYWORDS

Factuality checking; Eye tracking; Fake news

Further analysis shows that eye-tracking 25 users when reading 3-6 headlines is sufficient for our ensemble learner.

Eye tracking has long been used in IR to infer relevance [1, 3, 4, 7, 8, 11] and to improve user understanding, for instance that adding information to search engine snippets significantly improves performance for informational tasks but degrades performance for navigational tasks [5]; that users with higher change in knowledge differ significantly in terms of the number and duration of fixations compared to users with lower knowledge-change [2]; and that relevant documents tend to be continuously read, while irrelevant documents tend to be scanned [6]. In most cases, cognitive effort inferred from eye-tracking data is highest for (at least) partially relevant documents and lowest for irrelevant documents.

Our findings complement prior findings that news posts from credible sources receive more gaze attention [13] and that false news tends to be read more quickly than accurate news [6]. However, none of the above studies is done on headlines, and, to our knowledge, we present the first factuality inference model to be trained exclusively on eye-tracked data.

2 EXPERIMENT DESIGN

55 participants with normal or corrected-to-normal vision were recruited (24 females, 31 males; 19-33 years of age, median age 24), and each participated in a single eye tracking session in a laboratory. At the start of each session, we logged the age and gender of each participant and then introduced the task and apparatus. The eye tracker was calibrated and the task commenced. On completion of the task, participants were debriefed and comments were solicited. At no time were participants informed about how well they were doing. Each participant was shown a screen (white background) with three headlines (each on a separate line, in black font, size=36), without any further information. The headlines were centered on the screen, with 70mm of space between them and 20mm of space to the left border of the screen. Participants were asked to choose the most recent headline. This task was chosen on purpose to keep participants engaged in reading under circumstances where they were not directly checking for factuality. When participants had made their choice, the next screen (showing three new headlines) appeared. Participants did not know that two of the headlines were true and one was false, at any time. In total, 36 screens, each with three different headlines, were shown (108 unique headlines). To address order effects, we fully counterbalanced the position (top, middle, bottom) of the headlines, so that each position contained a factually false headline exactly 12 times. Participants could not move on to the next screen before answering, with no possibility of giving a “don’t know”-answer, and could not revisit a previous
screen. All participants saw the same 36 screens with the order of screens randomized across participants. No time limit was set for completing the task.

To calibrate the experimental design, we did a pre-study on 11 participants with a subset of 24 screens. The pre-study did not lead to any changes in the design or protocol, except that the number of screens was increased to 36 because participants were faster than initially expected. In our analysis we combine the data from the pre-study with the remaining data to form the complete dataset.

Each participant performed the task individually, and was given the same oral instructions by the research assistant. Participants could at all times elect to stop the experiment (none did). The study was approved by the ethics board of our university, and all data was anonymized prior to storage and analysis.

The headlines shown to participants were crawled from the website of a reputable local newspaper\(^2\) was anonymized prior to storage and analysis. All the semantic transformations we used to falsify headlines are (which are known to be fixated on by the human eye much more based eye tracker bar, paired with a 24-inch screen (resolution of 1920x1200 and 170 DPI). The eye tracker sampled the position of eyes at the rate of 30 Hz and had a spatial resolution of 0.1 degree. We used iMotions\(^3\) to calibrate the eye tracker and collect the data. Participants were placed 60cm away from the screen, and the room had soft standard artificial light. No head stabilisation was used (head movements were unconstrained so the intrusion of the eye moving measurement was minimal). We calibrated the eye tracker using a standard 9-point calibration prior to each recording.

Participants indicated which of the three headlines per screen was the most recent by typing 1, 2, or 3 on the keyboard (for the position of the top, middle, and respectively bottom headline). Typing was chosen over using the cursor because the cursor could interfere considerably with eye tracking.

**Eye-tracking measures.** A fixation is a stable eye-in-head position within a dispersion threshold (typically 2 degrees), above a duration threshold (typically 100-200 milliseconds\(^4\)), and velocity below a threshold (typically 15-100 degrees per second). Gaze duration is the cumulative duration of a sequence of consecutive fixations within an area of interest (AOI). We defined a separate AOI around each headline and we analysed these 5 measures: the total time spent fixating inside an AOI (total fixation duration); the total number of fixations inside a AOI (total fixation count); the total time spent gazing inside an AOI (total gaze duration); the average fixation duration inside an AOI (total fixation duration divided by total fixation count); the duration of the first fixation inside an AOI (first fixation duration).

### 3 FINDINGS

We now study the statistical effect the headline factuality has on the eye-tracking measures. Let \(y\) denote any of the above 5 eye-tracking measures. To establish whether factuality affects each of these \(y\)s in a statistically significant way, we consider both fixed effects (gender, headline length, position of headline on screen), and random effects. These fixed and random effects are potentially non-negligible, meaning that conventional methods for inferential data analysis, such as ANOVA and general linear regression are not applicable [8]. We therefore fit a mixed model [15] that uses the above \(y\)s as a response and the fixed effects as explanatory variables. Because each participant is drawn from some larger population, the participant is included as a random intercept. The mixed model for each of the above \(y\)s is:

\[
y = \gamma_{\text{true}} + \gamma_{\text{middle}} + \gamma_{\text{bottom}} + \gamma_{\text{male}} + \gamma_{\text{female}} + \gamma_{\text{length}} + \gamma_{\text{content}} + \gamma_{\text{language}} + \gamma_{\text{position}} + \gamma_{\text{screen}} + \gamma_{\text{participant}} + \varepsilon
\]

where \(\gamma_{\text{factor}}\) is the coefficient for the factor and \(\gamma_{\text{factor}}\) is the indicator function for the factor, e.g. \(\gamma_{\text{male}} = 1\) if the participant is male and \(\gamma_{\text{female}} = 0\) otherwise. For the categorical variables of position (middle, bottom), gender (male), and factuality (true), there are \(k - 1\) fewer factors than number of categories (\(k\)). \(l\) is the normalised length of the headline with zero mean and unit variance, \(p\) is the random effect for the participant, and \(b\) is the intercept. The model is fitted using the \(y\)s collected; these \(y\)s are normalised so that the scale of the coefficient is comparable across measures, which otherwise have different scales.

\(^{1}\)https://github.com/Varyn/Factuality_Checking_News_Headlines_EyeTracking
\(^{2}\)https://www.thelocal.dk/

Table 1: Dataset statistics.

|          | True | False | Total |
|----------|------|-------|-------|
| # Headlines | 72   | 36    | 108   |
| Mean # words per headline | 8.56 | 8.42 | 8.51 |
| Mean # content words per headline | 4.79 | 4.53 | 4.70 |
| Mean # function words per headline | 3.88 | 4.08 | 3.95 |

Table 2: All transformations that falsified news headlines.

| Original text | Transformed text |
|----------------|------------------|
| more, most, best, top, highest, good | fewer, least, worst, bottom, lowest, bad |
| denies, fear, pick up award, react to | admits, love, stripped of award, praise |
| two ... in top 50, remain, helping out | no ... in top 50, exit, refuses to help |
| criticised, leads in, drops down | praised, last in, tops |
| cannot get enough of, calls for end | do no like, tolerates |
| looks to ... as inspiration | uses ... as example to avoid |

\(^{3}\)https://imotions.com/
\(^{4}\)We set fixations at 100 milliseconds.
\(^{5}\)Gaze duration consists of the duration of fixations and other captured gaze activity (such as time between fixations) inside an AOI.
The coefficient $c_{\text{true}}$ shows the relation between the measure $\gamma$ and the factuality of the headline. We formulate the null hypothesis $H_0^\gamma$ for $\gamma$ as the assumption that factuality does not affect $\gamma$, that is $H_0^\gamma : c_{\text{true}} = 0$. To test this hypothesis, we compute $p$-values and confidence intervals for each coefficient by performing Wald tests. We have 5 different eye-tracking measures, so we perform 5 hypothesis tests with Bonferroni correction, requiring that $p < 0.05/5 = 0.01$ to reject each $H_0^\gamma$. All statistical analysis is done using StatsModels\(^6\), and the models are fitted using Maximum Likelihood.

Table 3 shows the resulting coefficients. We see that for total gaze duration, total fixation duration, and total fixation count $p < .001$, thus we have sufficient evidence to reject the null hypothesis. These three eye-tracking measures change significantly when reading true versus false headlines. However, for average fixation duration and first fixation duration, we cannot reject the null hypothesis, and thus we cannot conclude that the time spent on each individual fixation changes between factually true and false headlines. We also observe that a factually true headline causes the total gaze duration, total fixation duration, and total fixation count to increase, as seen by the positive value of $c_{\text{true}}$; this means that false headlines in general have shorter fixation and gazing duration than true headlines. The fact that factuality is not significant for average fixation duration means that the increased total fixation duration for true headlines is caused by an increase in total fixation count for factually true headlines.

We now briefly discuss the other coefficients than $c_{\text{true}}$. Using $p < .01$, we see that the position of the headline is not significant for the total gaze duration, while it is significant if the headline is placed on the bottom for all measures of fixation. The negative value of $c_\text{bottom}$ shows that all measures of fixation decrease when the headline is placed on the bottom. The length of the headline is significant for all eye-tracking measures ($p < 0.001$), with longer headlines having higher measures. Lastly, we observe no significant difference in any measures between the genders.

**Learning to infer factuality from eye tracking**. Having established that total gaze duration, total fixation duration, and total fixation count are all significantly different depending on the headline factuality, we next investigate if these measures provide sufficient signal for training a headline factuality classifier. As these measures are highly dependent on the length and position of the headlines, they are also included in the model. We observe that total fixation duration is highly correlated with total fixation count, thus to keep the model as simple as possible, we only use total gaze duration and total fixation duration.

In Table 3, we see the coefficient of factuality ($c_{\text{true}}$), for many measures, to be less influential than the position and length of the headline. Thus, we expect using eye-tracking measures of only a single participant to be noisy. Due to this, we use an ensembling approach, where the predicted factuality of a headline is computed as an average over a set of participants ($P_{\text{ens}}$): $\hat{v}_h = \frac{1}{|P_{\text{ens}}|} \sum_{p \in P_{\text{ens}}} v_{p,h}$, where $\hat{v}_h$ is the factuality prediction for headline $h$, and $v_{p,h}$ is the factuality prediction for headline $h$ for participant $p$. Due to the relative small size of our dataset, we propose to use the average of two simple second-order logistic models for estimating $v_{p,h}$:

\[
\begin{align*}
\hat{v}_{p,h}^1 &= \frac{1}{1 + e^{-\left(c_1 \text{top}(h) + c_2 \text{middle}(h) + c_3 \text{bottom}(h)\right)}} + c_4 \text{length}(h) + c_5 \text{total gaze}(h) + c_6 \text{total fixation}(h) + c_7 \text{total fixation count}(h), \\
\hat{v}_{p,h}^2 &= \frac{1}{1 + e^{-\left(c_8 \text{top}(h) + c_9 \text{middle}(h) + c_{10} \text{bottom}(h)\right)}} + \frac{\hat{v}_{p,h}^1 + \hat{v}_{p,h}^2}{2},
\end{align*}
\]

where $c_k, k \in \{1, 2, 3, 4\}$ are the learned coefficients of the logistic models, $y_{p,h}$ is the total gaze duration for participant $p$ on headline $h$, $y_{p,h}^\gamma$ is the total fixation duration for $p$ on $h$, and $l$ is the length of the headline. Both logistic models have one eye-tracking measure interacting with either the length or position of the headline, where the interaction is chosen based on the pair with the lowest correlation. We choose to use two simple logistic models, instead of a single combined model, to increase the variance of the predicted factuality, as high variance is beneficial for ensembling. We standardize (zero mean and unit variance) the eye-tracking measures from each participant across all headlines. Lastly, the two logistic models are trained using Maximum Likelihood on a set of training participants.

**Evaluation**. We evaluate the model by inferring factuality on unseen headlines using Monte Carlo cross-validation over 100,000 iterations. In each iteration, the participants are split for training and ensembling (27 and 28 participants, respectively), and three headlines are chosen for evaluation (2 true and 1 false), while the remaining headlines are used for training. We report the mean AUC and mean accuracy, across all iterations.

---

\(^6\)https://www.statsmodels.org/stable/index.html, version 0.9
Table 4: Factuality performance scores from our eye-tracking ensemble model.

| Mean AUC | Mean Acc. | Mean Acc. (True) | Mean Acc. (False) |
|----------|-----------|------------------|-------------------|
| 0.688    | 0.634     | 0.619            | 0.662             |

![Figure 1: Performance analysis when varying (left) the number of screens used for participant standardization in our model and (right) the number of participants used for ensembling.](image)

As reported in Table 4, we find that our ensemble model predicts the factuality of unseen headlines with a mean AUC of 0.688 and an accuracy of 0.634 (which is higher on false headlines (0.662) than one true ones (0.619)). There is no prior work on automatically detecting factuality in news headlines only, but related work on inferring factuality in text (but not headlines, which is harder) using textual features alone (not eye-tracking features), shows that accuracy ranges from 0.39 [14] to 0.76 [9], and even up to 0.86 [10] when using BiLSTMs and a multilayer perceptron classifier with refined linguistic features such as entailment and contradiction.

Comparably, we have a simple learning model, which uses weaker input features (eye-tracking measures are less discriminative than textual ones), and which solves a more difficult problem (factuality checking in headlines instead of longer texts).

**Analysis.** In the above, we standardize the eye-tracking measures for each participant on all headlines. We now ask: how important is this standardization, and would standardization on fewer headlines suffice? We answer this by sampling fewer headlines to base the standardization on, while still preserving the ratio of 2 true headlines for each false one. We refer to three headlines following this ratio as a "screen".

Figure 1 (left) shows the mean accuracy and AUC when varying the number of screens used for standardization. When only standardizing on the screen we predict on (screen=1), mean AUC is at minimum; it drastically increases at 6 screens, and then stabilizes for the remaining number of screens. When increasing the number of screens, the accuracy for the true headlines decreases slightly, while the accuracy increases for the false headlines, but after 6–18 screens the difference of including more screens is minimal. This suggests that the performance of our ensemble model is not largely dependent on a large set of headlines to use for standardization.

The results reported above correspond to splitting participants approximately 50/50 for training and ensembling, and this split can of course be varied; Figure 1 (right) plots mean accuracy and AUC (y axis) across a varying number of participants used for ensembling out of the 55 participants in total. We see that the choice of a 50/50 split is close to optimal. The fact that performance drops rapidly when 15 or fewer participants are used for ensembling indicates that aggregating over a large set of participants is at least as important as training a model on more data, in this setup. This happens because our dataset is small (we have few participants), so the optimal performance is a trade-off between training a better model (requiring more participants for training) and aggregating over more participants (requiring more participants in the ensemble).

4 CONCLUSIONS

We studied whether the human eye moves differently when reading factually true versus factually false news headlines, and if we can infer factuality in news headlines using only eye-tracking signals. In an experiment with 55 users reading 108 news headlines, we found that false headlines receive statistically significantly less visual attention than true ones. We used this to build an ensemble learner that predicts news headline factuality using only eye-tracking measurements, which obtained a mean AUC score of 0.688 and a mean accuracy of 0.634.

Future work includes investigation of eye tracking as a boosting mechanism to potentially improve factuality detection based on text processing, and refining the relationship between eye movements in more typical IR tasks such as search. A different direction of promising future work is to repeat our study "in the wild" outside usual laboratory settings, including eye-tracking methods with lower fidelity, such as for instance typical cameras mounted on laptops and smartphone cameras.

REFERENCES

[1] Anıtı Ajankı, David R. Hardoon, Samuel Kaski, Kai Puolamäki, and John ShaweTaylor. 2009. Can eyes reveal interests? Implicit queries from gaze patterns. User Model. User-Adapt. Interact. 19, 4 (2009), 307–339.
[2] Nilavra Bhattacharya and Jacek Gwizdka. 2018. Relating eye-tracking measures with changes in knowledge on search tasks. In ETIRA. 621–625.
[3] Georg Buscher, Andreas Dengel, Ralf Biedert, and Ludger V. Elst. 2012. Attentive Documents: Eye Tracking As Implicit Feedback for Information Retrieval and Beyond. ACM Trans. Interact. Intell. Syst. 1, 2, Article 9 (2012), 30 pages.
[4] Georg Buscher, Andreas Dengel, and Ludger van Elst. 2008. Query expansion using gaze-based feedback on the subdocument level. In SIGIR. 387–394.
[5] Edward Cutrell and Zhewei Guan. 2007. What are you looking for?: an eye-tracking study of information usage in web search. In CHI 407–416.
[6] Jacek Gwizdka. 2014. News stories relevance effects on eye-movements. In ETIRA. 283–286.
[7] David Hardoon, John Shawe-Taylor, Anıtı Ajankı, Kai Puolamäki, and Samuel Kaski. 2007. Information Retrieval by Inferring Implicit Queries from Eye Movements. Journal of Machine Learning Research - Proceedings Track 2 (12 2007), 179–186.
[8] Tomasz D. Loboda, Peter Brusilovsky, and Jörg Brunstein. 2011. Inferring word relevance from eye-movements of readers. In IUI. 175–184.
[9] Verónica Pérez-Rosas, Bennett Kleinberg, Alexandra Lefèvre, and Rada Mihalcea. 2018. Automatic Detection of Fake News. In COLING. 3391–3401.
[10] Adam Poliai, Jason Naradowsky, Aparajita Haldar, Rachel Rudinger, and Benjamin Van Durme. 2018. Hypothesis Only Baselines in Natural Language Inference. In Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics. Association for Computational Linguistics, New Orleans, Louisiana, 180–191.
[11] Kai Puolamäki, Anıtı Ajankı, and Samuel Kaski. 2008. Learning to learn implicit queries from gaze patterns. In ICML. 760–767.
[12] Keith Rayner. 1998. Eye movements in reading and information processing: 20 years of research. Psychological Bulletin 124, 3 (1998), 372–422.
[13] Michael Süßlow, Svenja Schäfer, and Stephan Winter. 2019. Selective attention in more typical IR tasks such as search. A different direction of research. In Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics. Association for Computational Linguistics, New Orleans, Louisiana, 180–191.
[14] Wiliam Yang Wang. 2017. "Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection. In ACL. 422–426.
[15] Lang Wu. 2009. Mixed Effect Models for Complex Data. Monographs on Statistics and Applied Probability, Vol. 113. CRC Press.