**Data Extraction Table**

Use this tale to support your synthesis of the literature you have read. You may wish to skim read your articles to gain this information or use the A-C method of reading articles. You may also wish to change the headings below to suit your type of discussion and analysis. You may wish to do a mind-mapping exercise first to establish the dominant themes and key areas you wish to compare and contrast.

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| Authors | Year | Country of Origin / Fieldwork | Study Purpose / Design / Setting | Methods | Findings | Discussion | Notes |
| Mohit Iyyer; Peter Enns; Jordan Boyd-Graber; Philip Resnik | 2014 | United States / Computer Science – Artificial Intelligence | **Political Ideology Detection Using Recursive Neural Network**  **Data:**  Convote  US Congress Debate Transcripts from 2005, speakers labelled with their Political Ideology. Debates separated into a sentence level approach. Low % of sentences contain explicit ideological bias. Used *Yano et al.* tool to select sentences more likely to contain an explicit bias, mainly through trigger-words[[1]](#footnote-1). Final dataset is a union of LIWC triggered sentences and Stick-Bigrams triggered sentences. Dataset equalised with Republican/Democrat 🡪 7,816 data points/sentences.  IBC  Annotated articles by authors with well-known political leanings. Same filtering procedure for Convote used here. 55,932 sentences. As the majority of sentences in IBC didn’t exhibit bias, dataset filtered further using DUALIST[[2]](#footnote-2) to reduce neutral sentences. DUALIST trained to classify neutral or biased on 200 sentences. Labelled 11,555 sentences as biased. Annotated by Crowsourcing (US and filtered using gold paths – obviously biased – before and during the annotation). An annotation is only kept if two annotators agree on it. 3412 sentences. | Experiment  Baselines:  *LR = Logistic Regression*  Random: Randomly chooses left or right label.  LR1: Uses only BoW features  LR2: Uses only BoW features + phrase level annotations as separate training instances (Only IBC)  *Offer a comparison to simple BoW models.*  LR3: Uses BoW and Syntactic pseudo-word features. Dependency relations specify properties of verbs.  *Contrasts traditional syntactic features with those learned by RNN model*  LR-w2v: Trained on the average of the pretrained word embeddings for each sentence. Allows comparison against a lexical representation that encodes syntactic and semantic information without the RNN structure.  RNN  Generate a feature vector for every node in the tree.  Percolate representations to the root of the tree.  Generate final instance representation: Concatenate root vectors and average of all other vectors.  Train an L2-regularised LR model over these vectors to obtain final accuracy numbers on the sentence level.  Report results for three different RNN settings *See section 2*. Perform 10-fold cross-validation on training data to find best RNN parameters:  RNN1: Randomly initialises all parameter, uses only sentence level labels.  RNN1-(w2v): Uses the word2vec initialisation for only sentence level labels.  RNN2-(w2v): w2v initialisation, includes annotated phrase labels in its training. Adds a new hyper-parameter beta to weight error at annotated nodes higher than the error at unannotated nodes. Meaning annotated nodes contribute more towards the objective function. | RNN models outperform bow baseline and w2v on both datasets. Increased accuracy suggests trained RNNs can detect bias polarity switches at higher levels in parse trees.  Phrase levels did not improve baseline performance but did improve RNNs 🡪 Allowing RNNs to correctly predict more complex sentences.  Obtained better results on Convote then IBC with all models.  Convote has a larger dataset.  Convote sentences were originally spoken, they are shorter.  RNNs do not perform as well with longer sentences 🡪 information is lost. | Apply RNN to political ideology detection 🡪 outperformed previous benchmark (BoW).  Approach to crowdsourcing successful as well as sentence and phrase level. |  |
| Arkajyoti Misra;  Sanjib Basak |  | United States | Political Bias Analysis  **Data**  IBC: Sentence-Level, Hand Picked by Iyyer to be expressive of political sentiment.  OTI: *On The Issues*: collects political speeches, dialogues, debates. More expressive of the speaker’s bias compared to the previous data set. Separated sentences based on their issue. Labelled not on the political affiliation of the speaker but on the bias the speech represented. | Conventional RNNs struggle to back propagate the gradient over many timesteps, leading to vanishing and exploding gradients over longer form text. LSTM model is used.  Binary Classification is used : ROC-AUC and F1 score will be used to evaluate.  Baseline set using BoW 🡪 Performed poorly on both datasets.  Single Layer LSTM of varying units, Adam Optimiser, Binary Crossentropy Loss. Optimiser ran for unlimited epochs, 10step early stopping scheme to terminate model runs. Batch Size: 32.  5-fold cross validation used, each fold trained on 80% of the data, validation score calculated for the remaining 20%. | IBC:  Model fitted well, validation loss increased slowly. Likely due to training data differing from validation data. Embed size: 20-80, Dropout Rate 0.05-0.3  Best F1: .568 hidden size of 40, dropout rate of 0.05  Poor performance is still good when compared to Isroy et al.  Better results of Iyyer may be due to manually labelled nodes. *Not scalable*.  OTI:  Didn’t have to resort to a low dropout number. Best performance peaked at .9. AUC had an opposite trend but who cares right?  Learning rate being doubled didn’t impact the model too much. Smaller HL size and faster learning rate together did impede performance.  Bi-Directional 🡪 Very Good to try, they didn’t find anything. | LSTM could predict implicit bias in text even if there are no specific words present in text that relates to either party.  Model performed poorly on IBC – little overlap of contents. However, most didn’t show any human-detectable bias anyway. Iyyer work more successful, however theirs was measured with accuracy rather than F1 and was annotated at phrase level.  OTI (Larger breadth scale) was very successful 🡪 Collated data achieve .718 F1 score. Best accuracy when compared to rest of the literature.  LSTM only slightly outperforms BoW, is better with more data to process. |  |
| Kulkarni, Vivek; Ye, Junting; Skiena, Steven; Yang Wang, William; | 2018 | United States | Other reports generally only process the text in articles. However, online news articles contain a rich structure of information. These information points (such as article title) can also be used to detect political bias. Also links to other news sources, which is likely to be sources of a similar ideology. Using a Multi-View model (MVDAM) can increase accuracy of detecting political bias.  Data  Using Data from ALLSIDES.COM, obtain a list of 59 news sources and their political ideology (Left, Center, Right). *Unbiased -> Blind Survey to rate bias*.  Extracted content from a fixed time period. For each source, extract title, cleaned pre-process content, hyperlinks within the article that reveal the network structure. Labelled with information from ALLSIDES.  Cleaned: Remove source link mentions to avoid over-fitting. Remove any link structures in articles that are source specific e.g. social media links. Remove Headers, Footers and advertisements. | Bayesian Model with stochastic attention units used to effectively model textual cues 🡪 effective at modelling ambiguity as well avoiding over-fitting scenarios.  Latent representation h 🡪 Instea of learning a deterministic encoding.  P(h|X) parameterized by diagonal gaussian distribution.  Title  Modelled using a CNN. Input words mapped to word embeddings and concatenated and passed through convolutional filters of varying window sizes. Output of this layer fed to a fully collected layer of dimension d which outputs ztitle (latent representation of the title).  Article Links  Must learn network representation of each source based on links graph and use learned representation of each source to capture the link structure of an article.  Representation of nodes in social network performed using Node2Vec, outputs a d-dimensional representation given hyperlink graph G. Link structure calculated by averaging all linked vectors in the representation.  Article Contents  Hierarchical approach. Compute attention at word-level and sentence-level. Approach learns a latent representation of both word and sentence attention models. Model article by |  |  |  |
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1. Linguistic Inquiry and Word

   Count lexicon (LIWC) (Pennebaker et al., 2001), lists of “sticky bigrams” (Brown et al., 1992) [↑](#footnote-ref-1)
2. (Settles, 2011) [↑](#footnote-ref-2)