Ideology Detection in the Indian Mass Media

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Mass media is an important apparatus for shaping public opinion. Any bias prevalent in the policy discourse in mass media can thus have a significant impact on how people understand policies. In this study, we aim to understand the ideological bias existing in Indian mass media, in terms of the coverage it provides to the statements given by influential people on key economic and technological policies. We adopt a hierarchical methodology using Recursive Neural Networks to model the semantics of these statements. Our results show that the Indian media is ideologically biased, typically covering pro-policy statements much more than anti-policy statements and favoring a technology deterministic viewpoint more than the other side of the discourse. Alongside estimating the ideological differences existing among these influential people or entities on these policies, we are also able to make a generic policy-level classifier that can push the media towards self-regulation in terms of achieving diversity in the policy discourse.

Additional Key Words and Phrases: Ideology Detection, Social Policy, Media Bias

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1 Introduction

Several studies [9, 19, 22] have proven that mass media might be biased towards or against a particular government, political party, or ideology. Assessing media bias is thus an essential need since the mass media is known to significantly shape public opinion [16] and the social context in which the policies are developed. In this paper, we study the ideological bias carried by the Indian mass media, in terms of the statements that it covers on important economic and technological policies. These statements are often made by influential people (or entities) who might be in favor of or against a policy. In other words, these statements help us understand the ideological positions of the entities on policy issues. The preferential coverage provided to these entities and their statements, in turn, helps us understand the ideological bias of the mass media.

For political statements, such ideological positions may be localized to a particular part of the sentence. Existing approaches on sentiment analysis prove to be insufficient for this task of ideology detection, since they often fail to pick up complex linguistic features that explain ideological positions, like sentence structures, negations, and contextual information. For example, SentiStrength, a popular tool for sentiment analysis, classifies the statement, *"Just because it is possible to hack a network does not mean that technology must not be deployed."* as a negative sentiment statement even though it is a pro-technology statement. Similarly the statement *"Earlier farmers used to get insurance of Rs 50,000 on death or permanent disability under Raj Sahakar Personal Insurance Scheme, which now has been increased to Rs 10 lakh."* requires information of the domain of discussion to predict that increasing the insurance amount for farmers is a positive outcome. Hence, ideology detection of such statements requires us to understand the context of the sentence rather than considering the sentence merely as a bag-of-words.

In this work, we use natural language processing and deep learning to analyze Indian mass media articles on major economic and technological policy events. Our primary contributions are:

(a) Two annotated datasets containing 3855 and 812 statements related to economic and technological policies, respectively (refer to table 2 for details). (b) Two fine-grained stance detection models to study if a statement is in favor of or against an economic or technological policy, and their application on the Indian mass media data to understand the underlying ideological bias accurately. We also show that our stance detection models are generic enough to be applied to new policy data as well.

Our ideology detection framework has been shown in figure 1. It consists of three main components:

- **Data Extractor**: This module extracts statements made by different entities from articles on specific policies.
- **Relevance Filter**: This module filters out the non-relevant statements extracted in the previous step.

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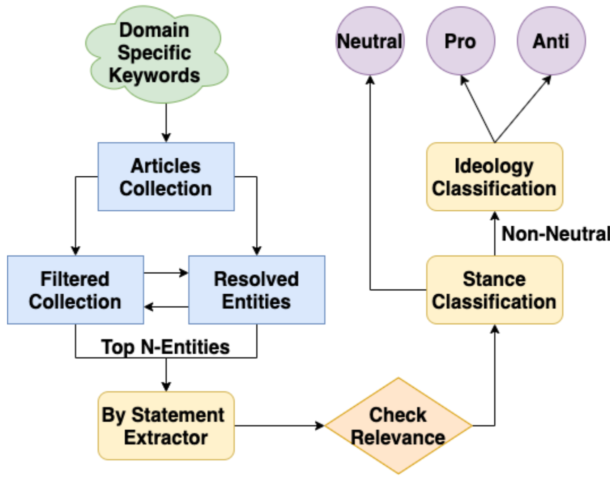


Fig. 1. Our proposed Ideology Detection Framework

- **Classifier**: This module consists of a two-step classifier that first checks if a statement is neutral, and then checks if the non-neutral statement is in favor of (pro) or against (anti) the policy.

We develop a two-step classifier using a recursive neural network at each step. Our classification approach is entity-independent, i.e., it does not depend on the affiliation or ideology of the entity (like a politician affiliated to a certain political party) that makes the statement. For this purpose, we use a method of preprocessing the data to obtain fine-tuned word vectors whose meanings are not associated with the ideology or affiliation of an entity. Our aim is to build an umbrella classifier that can be applied to different datasets or policies. Hence, we adopt a method of training procedure that ensures generalizability on new policies. We do this by freezing the embedding layer of the model while training, and also ensure that the dataset used for training the model has enough domain information for the classifier to learn various common axes of economic or technology policy debate and evaluate any other economic or technology policy on these same axes. The details of the model, the fine-tuning approach, and the training process are described further in section 6.

We use this framework to study the ideological biases in the Indian mass media in terms of the policy-related statements that they cover. Our findings show that the Indian mass media typically covers pro-policy statements much more than anti-policy statements, and covers pro-technology viewpoints much more than the other side of the discourse, indicative of an ideological bias existing in mass media. We also demonstrate how our framework is generic enough to be applied to any other domain of ideology classification.

2 Related Work

There has been extensive work on political-ideology detection through natural language processing. Sentiment analysis techniques have been used in some works to identify the ideology of a particular statement. The traditional methods include use of partisan tokens [9] and bag-of-words [10] for ideology detection. In one of the earliest works in this field, Gentzkow and Shapiro [9] developed a "slant-index" that quantifies media slant, by analyzing key phrases in the news content specific to political ideologies. Apart from a domain-specific phrase or word detection, researchers have also leveraged various sentiment analysis tools like Sentistrength, Vader, Alchemy, etc. to analyze the sentiment exhibited in text. While these works give strong evidence of media being biased, by showing a correlation between newspaper-slant and ideology of its potential readers [9], and showing how media bias affects voting pattern [10], such approaches are too coarse to understand the political ideology resulting from the use of complex evidence and words in a particular context. These tools are based on the presence or absence of certain words which are clearly indicative of a certain sentiment. For example, the word "good" contributes towards a positive sentiment, and the word "bad" contributes towards a negative sentiment. Quite often, such tools ignore the sentence structures, negations, and contextual information, which also play a key role in determining the overall stance of the statement. Most of the conventional techniques essentially focus on bag-of-words models which ignore the syntax. Mullen et al. [20] show that such traditional text classification techniques are inadequate for the task of political sentiment analysis. This can be attributed to the arbitrariness in the statements belonging to a particular class of policies. Yan et al. [35], on similar lines, show that generalizing across different datasets or policies, and making an umbrella classifier is extremely difficult as concepts are significantly distinct across policies.

More sophisticated approaches towards political sentiment analysis include Hidden Markov Model (HMM) based models [28] and hierarchical topic modeling [21]. Sim et al. [28] propose an HMM-based model, which uses a fixed lexicon of bigrams to infer the ideology used by political candidates in their campaigns. Inspired by a two-level political science theory, which unifies agenda setting and ideological framing, Supervised Hierarchical Latent Dirichlet Allocation (SHLDA) [21] is seen to improve prediction of political affiliation and sentiment. More recent works include the use of machine learning and deep neural networks for natural language processing, which have proved to be effective in incorporating the complicated nuances of language. They therefore predict the correct sentiment accurately. For example, Budak et al. [6] use crowd-sourcing and machine learning techniques to understand whether or not the US media reports in a non-partisan manner. Iyyer et al. [11] have used recursive neural networks (RNNs) to detect political ideology at the sentence level. Inspired from their work, we have built a Recursive Neural Network based model for ideology detection in economic and technological policies. The difference of our work from the aforementioned studies is that we develop a two-step classifier with a training procedure that ensures generalizability on new policies, and a method of fine-tuning to initialize the embedding layer, which makes classification entity-independent.

3 Background

In our study, we analyze mass media bias corresponding to four economic policies, and a group of technological policies hereinafter referred to as *technology policies*. We build two classifiers to identify the ideology of a statement - *Pro* versus *Anti* for economic policies, and *Determinism* versus *Skepticism* for technology policies.

3.1 Economic Policies

The economic policies that we study in this work are Aadhaar, Demonetisation, GST, and Farmers' protests since these are recent, contentious, and of national importance [3]. Under the *Aadhaar* policy, the government took the initiative to assign every Indian resident a biometric-based unique identification number. The policy has been criticized owing to lack of security and privacy in citizens' data collection and storage mechanisms, and allegedly faulty implementation of the platform [8]. Under *Demonetisation*, the government on 8 November 2016 banned all 500 INR and 1000 INR banknotes with the motive of curtailing the use of illicit and counterfeit cash used to fund illegal activity and terrorism. The move was widely criticized owing to multiple problems caused to common people due to sudden depletion of liquidity, irregularities in norms of exchanging old currency notes, and cash exhaustion [13]. *Goods and Services Tax (GST)* is an indirect tax levied in India on the sale of goods and services at each step of the production value-chain with an effort towards formalization in the industry. There have been intense debates on its complexity and problems in implementation, which have impacted the overall growth of the economy [7]. *Farmers' Protests* covers agricultural issues and a series of protests by farmers in India, including the ones at Madhya Pradesh (Mandsaur protest) and Maharashtra (Kisan long march) demanding better prices for crop production, loan waivers, etc. [2].

A statement can be classified into different categories based on the political ideology it holds. A *Pro* statement is where the speaker is in support of the policy or appreciates the policy (e.g. *"Aadhaar project is an example of using modern technology to leapfrog for future development."*). *Anti* statements are where the speaker criticizes the policy or talks about its drawbacks (e.g., *"Despite waiver, banks have still not started disbursing fresh credit to farmers leaving them starved."*). *Neutral* statements do not have a specific stance (e.g. *"Speaking at the opening ceremony, Shukla said, the BCCI is committed to the welfare of farmers."*). There also are some statements that are diplomatic in nature and hold both *Pro* and *Anti* stances. We collectively group such statements into another class called the *Balanced* statements. The Pro/Anti Econ classifier takes as input an economic policy related statement made by an entity and outputs whether it is in favor of (pro) or against (anti) that policy.

3.2 Technology Policies

Technology policies refer to a group of policies that include various technical interventions aimed at solving problems of the people. It includes several key policy issues like Cashless Economy [30], Digital India [31], E-Governance [32], and Aadhaar. *Cashless Economy* aims to create an economic state whereby financial transactions are not conducted with money in the form of physical banknotes or coins, but rather through the transfer of digital information between the transacting parties. *Digital India* is a campaign launched by the Government of India, which includes plans to connect rural areas with high-speed Internet networks.

Table 1. Policies and the set of augmented keywords to extract articles from mass media

Policy	Keywords (Manually Selected)	No. of articles
Demonetisation	demonitisation, demonitization, denomination note, cash withdrawal, swipe machine, unaccounted money, withdrawal limit, pos machine, fake currency, digital payment, cash transaction, cashless economy, black money, cash crunch, currency switch, long queue, demonetised note, cashless transaction, note ban, digital transaction	22302
Aadhaar	aadhar, aadhaar, UIDAI, adhar, adhar card, aadhar card, PDS, public distribution system	13908
GST	gst, gabbar singh tax, goods service tax, goods and services tax	22179
Farmers' Protests	farm loan, crop loan, farmer suicide, debt waiver, waiver scheme, farming community, farmer agitation, plight farmer, distressed farmer, farmer issue, farmers' protest, farmers' protest, agrarian crisis, agrarian unrest, farmers protests, farmers' protests, loan waivers, loan waiver, agriculture protest, farmers' march	85486
Technology	privacy, cashless, technology, technological, innovation, software, engineering, smart city, technical, data protection, big data, artificial intelligence, digital india, high speed internet, make in india, e-governance, umang, digital literacy, national policy on electronics, e-gadget, entrepreneur, startup, scientific, science	23432

The *National e-Governance Plan (NeGP)* is an initiative of the Government of India to make all government services available to the citizens of India via electronic media, instead of them having to fill up paper forms.

A technology related statement can be categorized under different groups depending on its ideological position. *Pro* technology (Technology Determinism) statements are where the subject shows faith in technology [33], and often suggests technology as the solution to people's problems (e.g., *"Mr. Modi told media leaders that digital technology can help in innovation and empowerment."*). *Anti* technology (Technology Skepticism) statements show doubt and skepticism about using technology, or the problems with its implementation. (e.g., *"Matching such state-of-the-art systems could be a technological nightmare for Indian counterparts."*). The Tech Determinism/Skepticism classifier takes as input a technological intervention related statement made by an entity and outputs whether it shows faith (determinism) or doubt (skepticism) towards that intervention.

4 Data

We analyze policies and events of national importance, which have been widely discussed and debated in the mass media. Our analysis pipeline contains a number of steps similar to those described in Sen et al. [25]. We collect mass media articles on a daily basis from the websites and archives of popular national news-sources in English: *The Times of India, Indian Express, The New Indian Express, Telegraph, Deccan Herald* and *Hindustan Times*, that form an article collection since 2011. Apart from articles, we also store meaningful contextual information associated with each article including author information, language and relevant topics. Our pipeline also consists of several other key stages like named entity extraction from the collected articles (using OpenCalais [1] tool), live resolution of these entities, and extraction of statements made on the policies by these entities. We are currently using English language news sources for our analysis since Open Calais only works for English. However, we aim to expand our work on vernacular media sources too in the future. The ER component works at 97.61% precision and 96.47% recall for person entities, and 93.82% precision and 96.2% recall for non-person entities.

4.1 Collection of Articles

The media corpus that we build using the news article crawlers consists of articles belonging to the categories: National, International, Regional, Sports, Opinion and Business. In order to extract a subset of articles relevant to a particular policy from this set, we filter the entire collection of articles with some domain-specific keywords. To identify news articles about a topic, we first supply a list of manually selected keywords corresponding to each policy. After extracting articles containing these keywords, the keyword set is expanded with newer keywords from these articles, based on their frequency. These two steps are repeated iteratively until the keyword set becomes static, and the final set of articles is used to perform our analysis. The final set of augmented keywords for each policy is shown in table 1.

For the economic domain, we perform our analysis on 22,302 articles on Demonetisation (Nov 2016 to Oct 2019), 13,908 articles on Aadhaar (2011 to 2019), 22,179 articles on GST (Jan 2011 to Oct 2019) and 85,486 articles of Farmers' Protests (Nov 2016 to Oct

Algorithm 1: *By-statement* Classification of a given text

```
// Text: Text statement obtained after splitting
// EntName: Entity Name whose by-statements to extract
// Keywords: List of entity-specific keywords
// Aliases: List of different aliases used for a given entity
// FixedWords: ["says", "said", "asked", "told", "claimed", etc.]
Input: Text, EntName, Keywords, Aliases, FixedWords
Output: Classified Label (By/About/Others)
shortName ← Short Entity Name for EntName
Replace all Aliases occurences in Text with shortName
pText ← Dependency Parse Tree of Text
Tags ← Identify noun chunks (nsubj, dobj) in pText
posText ← POS Tagging of Text
for pt in pText do
    check1 ← if pt is related by one of the Tags
    check2 ← if corresponding posText entry is in Keywords
    if check1 and check2 then
        check3 ← if pt is a part of an 'nsubj' relation
        check4 ← if corresponding pText is in FixedWords
        if check3 and check4 then
            return "By"
        else
            return "About"
return "Others"
```

2019). The periods for Demonetisation and GST were identified around the immediate months when the policies came into effect. Aadhaar and Farmers' Protests have had long standing debates, and therefore a longer period of time was used for these topics. Following a similar methodology, we were able to extract 23,432 articles (Jan 2014 to Oct 2019) relevant to technology policies.

4.2 *By-statement* Extraction

To understand the ideological bias carried by news-sources, we need to extract the statements made by influential entities on the policy issues in these news-sources. These entities include politicians, business-persons, bureaucrats, social activists, and others. Statements on policies that occur in article text can be divided into three classes: the *by class* (containing statements made by the entities covered in media), the *about class* (statements made by the media house about the entities), and the *Others class* (statements that are neither spoken by the entities nor are about the entities). We perform entity resolution (ER) of these entities, which results in the identification of various aliases used to refer to an entity, along with various other entity-specific keywords. For example, the aliases found by the ER process for the current Prime Minister *Narendra Modi* are *Modi, NaMo, Modi Ji,* etc. and the keywords identified with him are *PM, Prime Minister, Gujarat CM* (since he is a former Chief Minister of Gujarat), etc. For a given entity, using the entity-specific keywords and aliases, we can sample out the by-statements by following the Algorithm 1.

We elaborate the algorithm here in some detail: firstly, for every article associated with a given entity name, all occurrences (or aliases) of the entity in the article are replaced by short, entity-specific tags (e.g., the aliases of the entity *Narendra Modi* can be *Modi*, *Modi ji*, *Namo*, etc. which are then replaced by the tag "narendra-modi" in the article). We then use Stanford CoreNLP [15] to obtain the parts-of-speech (POS) tags and dependency parse tree of the statement made by that entity. Sen et al. [25] have shown that several key dependency relations like 'nsubj', 'nmod', 'amod', etc. can be used to identify the class to which a statement belongs (by, about, or others). We also check if the object or the subject in the statement is connected to keywords like 'said', 'claimed', 'announced', 'told', etc. in the parse tree, which indicates that the statement belongs to the *by* class. These *by-statements* are then finally returned by the algorithm.

4.3 Relevance Filtering

Since we use a keyword-based approach to extract articles on a policy, we find that some statements in these articles do not talk about the policy, despite containing a keyword relevant to it. Such statements need to be removed from our final dataset used for ideology classification. For example, a statement like *"I concede defeat and congratulate Ananth Kumar for his performance in this*

Table 2. *By-statement* Distribution for various policies for the ground truth data after manual annotation

Domain	Policy	Total Statements	Relevant Statements					Total Relevant	Non-Relevant Statements
			Pro	Anti	Neutral	Balanced	Total		
Economic	Aadhaar	392	169	34	146	1	350	3855	42
	Demonetisation	1255	512	259	243	49	1063		192
	GST	681	292	145	167	46	650		31
	Farmers' Protests	1899	961	505	262	64	1792		107
Technology		1075	553	115	134	10	812	812	263

Table 3. F1-Scores for Relevance Check by various methods

Policy	Rule Based Approach			Supervised	
	nsubj	***+ dobj***	***+ pobj***	**Random Forest**	**Gradient Boosting**
Aadhaar	0.58	0.69	0.91	**0.95**	0.91
Demonetisation	0.29	0.57	0.85	**0.92**	0.85
GST	0.46	0.62	0.94	**0.98**	0.97
Farmers' Protests	0.36	0.62	**0.93**	0.92	0.84
Technology	0.25	0.51	0.77	**0.80**	0.75

poll," Nilekani, the face of UPA's flagship Aadhaar programme, told PTI." is irrelevant to Aadhaar. It, however, gets extracted since the keyword *Aadhaar* appears in it. We use an annotated dataset (ground truth) for the relevance-based filtering process, which has been created through manual inspection. 10.7%, 15.3%, 4.55%, and 5.63% of the statements in Aadhaar, Demonetisation, GST, and Farmers' Protest were found to be irrelevant, respectively. Similarly, there were 24.4% irrelevant statements for the Technology policies. We now elaborate on the different methods that were tried out to filter out irrelevant statements.

H. C. Wu et al. [34] has shown the significance of TF-IDF (Term frequency-inverse document frequency) term weights in making "document-wise" relevance decisions. Similarly, we converted our *by-statements* into TF-IDF vectors under the supervised approach. We perform binary classification of these statement vectors using various non-neural machine learning algorithms like SVM, Random Forests, and Gradient Boosting. Our corpus consists of an equal number of relevant and irrelevant statements. From multiple policy distributions, we found that Random Forest (RF) works the best mostly. We also try a rule based approach of checking relevance by analyzing relationships between the subject and the object tags in the dependency parse tree of a *by-statement* – we observe that the statements that contain 'nsubj'/'dobj'/'pobj' dependencies, and domain-specific keywords in their noun-chunks are usually relevant. A sample statement: *"At UIDAI, we are concerned about the privacy issue."* has been parsed using the built-in dependency visualizer of spaCy in figure 2. The figure shows some of the important entities related by the object and subject tags in red boxes. Since RF turns out to be the most robust in terms of F1-Scores among all these methods, we choose to deploy an RF-based pre-trained model for checking relevance. We are able to achieve an F1-Score of 0.95, 0.92, 0.98 and 0.92 for economic policies of Aadhaar, Demonetisation, GST and Farmers' Protests respectively, and 0.80 for Technology policies, using RF. Performance comparison between these methods in terms of F1-scores has been described in table 3.

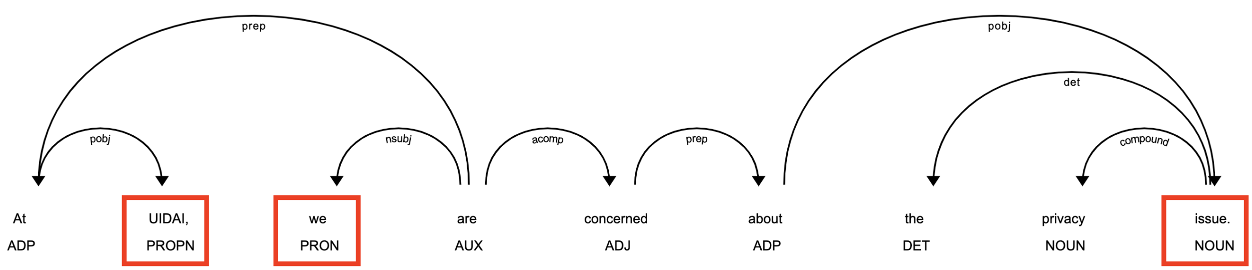


Fig. 2. Dependency Parse Tree for a By-Statement

5 Research Problem

We classify these *by-statements* into different classes (ideological positions) depending upon the policy domain (Economic/Technology) in which they lie. Examples of *by-statements* can be found in the supplementary [4]. We wish to study the ideological bias carried by Indian mass media in terms of Pro, Anti, and Neutral statements on important economic and technological policies. In this direction, we aim to use natural language processing with deep learning to build a classifier that can detect the stance (neutral/non-neutral) and classify the ideological position (Pro/Anti) held by influential entities that make statements on policies in the mass media. We also target to keep our methodology generalizable so that our models can also be applied to any other policy domain. More specifically, we enlist the two key problems that we target: (A) Our aim is to build a general pro/anti economic policy classifier, which does not require a dataset for each new policy for which it performs classification. In other words, we want to build a model that trains on a subset of policies and learns the various common axes of economic debates, and then classifies the statements belonging to any other economic policy on these same axes. (B) Similarly, our goal is to create a general pro/anti technology classifier to evaluate the degree of tech determinism or skepticism prevalent in our mass media sources. We aim to build the model using a small subset of policies concerning the technological domain, from which it can learn the pattern to classify any new interventions in the tech-policy area accurately.

5.1 Dataset Annotation & Coding Schema

With the help of our research group, we first manually code the *by-statements* to one of the five classes - *Non-Relevant, Pro, Anti, Neutral*, and *Balanced* using a coding schema that we describe further in thisw section. We resolve ambiguous cases using the context information that we preserve while extracting the *by-statements*. The context information includes the preceding and succeeding statements corresponding to each *by-statement* in the format ⟨*preceding-statement*, *by-statement*, *succeeding-statement*⟩. For example, for the sentence, *"The technology has undergone a drastic transformation in the last 20 years, Modi said adding the aspirations of the youths have to be kept in mind in this era"*, the following is the context information being stored using the script: (*"The PM said India's economy is being transformed and the manufacturing sector is getting a boost."*, *"The technology has undergone a drastic transformation in the last 20 years, Modi said adding the aspirations of the youths have to be kept in mind in this era."*, *"On merits of democracy, the Prime Minister said, Bigger than the strength of the government is the people's power."*). Here, if we consider the words, 'boost' in the preceding statement and 'the effect of technology' on the economy and manufacturing sector, the statement appears to be Pro-Technology.

We construct a coding schema that helps the annotators code the statements to one of the five classes (Non-Relevant, Pro, Anti, Neutral & Balanced). The use of a coding schema to unambiguously code data is quite widespread in the field of qualitative content analysis [5, 29]. In our case, the goal of the schema is to guide an annotator to understand if a *by-statement* conveys an ideology about a policy. For each policy, the schema contains the possible targets of a policy statement and the frequently occurring keywords with suitable examples for each class label. It helps the annotators accurately code any new statement on a policy. A normative definition of each class is also provided to help the annotator understand the general intuition of the class before labeling. The coding schema has been built after manually studying roughly 100 articles from each policy event (a manageable size of 400 articles in total) by the lead authors of this study, assisted by two annotators. After multiple rounds of due deliberation to reduce subjectivity, the coding schema is finalized and given to the rest of the annotators to perform the final labeling. The inter-coder reliability (using Cohen's Kappa statistic [17]) of the labeling exercise, which was evaluated by taking a random sample of 100 statements from different policies by three annotators pairwise, comes out to be roughly 0.75-0.79. It means that our gold set of labels is reliable and robust enough for various analytical experiments. Our coding schema for all the policy events can be found in the supplementary material [4].

6 Ideology Detection

In this section, we describe our framework to detect the political ideology of a particular *by-statement.*

6.1 Model

We use a two-step classifier to predict whether a statement has *Pro*, *Anti* or *Neutral* alignment for a policy. The first step – *stance detection* – is to determine whether the statement holds any stance concerning the policy or not, i.e., whether it is neutral or non-neutral. The second step – *ideology classification* – aims at classifying whether the statement is in support of the policy or against it, in case it is non-neutral. Models built for both of these steps have the same architecture and training method.

We use Recursive Neural Networks (RNN) inspired by Iyyer et al. [11], as our predictive model. They are a type of hierarchical neural network which take into account both the syntactic and semantic features of the sentence. They work on the assumption that the meaning of each phrase should be a combination of the meaning of the words that form it and the syntax that combines these words. Each phrase of a sentence can represent different ideologies, which combine to reflect the overall ideology portrayed by a sentence. The structure of the RNN takes this into account by first predicting ideologies of the phrases at a low level and then combining them with learned weights in a bottom-up manner to predict the ideology of the overall sentence. This kind of a network takes into account the structure of a sentence as well as the meanings of its individual words. This makes it effective as compared to other approaches that are based on the absence or presence of certain words or phrases in the sentence. It is also more effective than the approaches which use HMM-based models, since it combines information in a hierarchical rather than a

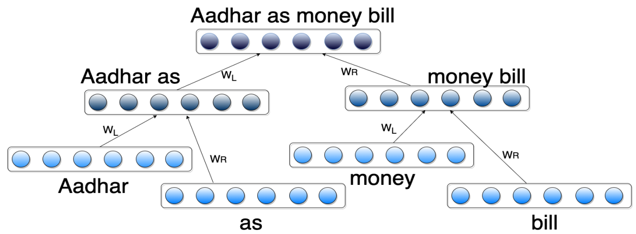


Fig. 3. Example of how word representations are combined to form phrase vectors of the same dimensions

linear manner, thus building the meaning of a sentence from its relevant phrases. Since it was not feasible to annotate each phrase of a sentence, we assume that the label of a phrase is the same as that of the *by-statement* in which it occurs. To break the sentence into phrases, we use the Stanford Parser to obtain the parse tree of the sentence, which is fed to the model as the input.

To represent the phrases of the parsed sentence as vectors, embeddings of words forming a particular phrase are combined to form a *phrase vector* (figure 3) that has the same dimensions as the word embeddings. If two words w_a and w_b combine to form a phrase p, then the vector representation of the phrase x_p is given according to the equation: $x_p = f(W_L.x_a + W_R.x_b + b_1)$ where x_a and x_b are the word embeddings of w_a and w_b, derived from an embedding matrix W_e of dimension $d \times V$, V being the size of the vocabulary. f is a non-linear activation function, W_L and W_R are the left and right composition matrices of dimension $d \times d$, and b_1 is a bias term of dimension $d \times 1$. The ideology of each phrase is then calculated as: $\hat{y}_p = \text{softmax}(W_{cat}.x_p + b_2)$ where W_{cat}, b_2 are parameters of dimension $2 \times d, 2 \times 1$. We use a cross-entropy loss function for training. The final cost function consists of a sum of the losses over all the statements in the corpus. Because of a small-sized dataset, we use $L2$ regularisation to avoid overfitting. The parameters of the model are optimized using Stochastic Gradient Descent with momentum.

To estimate the performance of the overall model, we employ macro-averaged F-score $F_{macro} = \frac{F_{Neutral}+F_{Non-Neutral}}{2}$ at Step-1 (stance detection) and $F_{macro} = \frac{F_{Pro}+F_{Anti}}{2}$ at Step-2 (ideology classification).

6.2 Word Representation

We use the embedding matrix from word2vec [18] pre-trained on the Google News corpus to initialize the embedding layer of the model. We have two choices while training the model: to train the embedding layer along with the whole model or to freeze this layer while training. We choose to do the latter as we do not have enough training data to learn good representations of words while also ensuring a model with good performance. The results in section 7 bolster this claim by showing a better model performance with a frozen embedding layer. While freezing this layer, we rely on our assumption that the initial embedding layer matrix gives a good enough representation of the word , requiring no additional training. However, as also shown in section 7, simply using the pre-trained vectors does not perform well, since ideology detection is a complex task that requires fine-grained embeddings, which are aware of the political context in which a word is used. For example, words like “digital” and “smart” have a very fine-grained meaning in this domain as they are more likely to refer to the policy interventions like *“Digital India”* and *“Smart Cities”*. Hence, we take the pre-trained Google News embeddings and fine-tune them before feeding them to the classifier without using any additional supervision. This is done by re-training a word2vec model, initialised with the pre-trained embeddings, on domain-specific policy corpus. We use two collections of articles, one about economic policies and another about technology policies, to fine-tune the word embeddings for economic and technology classifiers, respectively, which are then used to initialize the first layer of the model.

6.3 Making classification entity-independent

There is a reasonable improvement in the performance of the classifier when fine-tuned embeddings are used. To understand its effects on the performance, we also look at some examples which are being misclassified while using fine-tuned embeddings but are correctly classified when using general-purpose embeddings. We find that fine-tuned embeddings of entities exhibit associations with certain words. For instance, words supporting a policy have more association with ruling party entities (who rolled out the policy) compared to opposition party entities. We also find that dominantly anti-policy words associate significantly with entities of a specific religious group. Such associations often mislead the classifier into almost always favoring the ideology held by the entities while ignoring the hidden semantics of their statements. The process also captures undesirable associations such as caste and religious stereotypes.

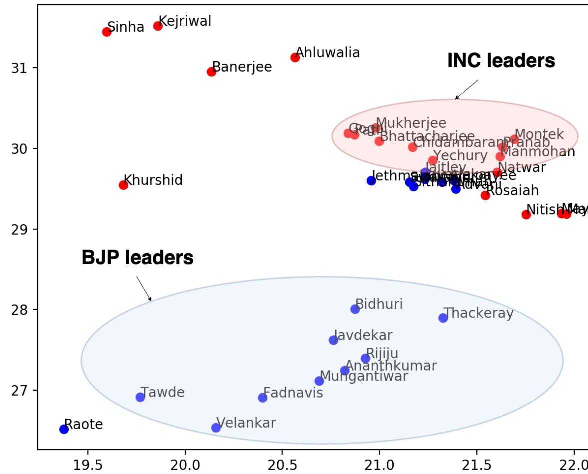


Fig. 4. Leaders in support (blue) & opposition (red) of economic policies

Figure 4 qualitatively shows some of the associations by visualizing the representations through a t-SNE plot. As shown, leaders in support (mostly of the ruling party, BJP) and in opposition (mostly of the opposition party, INC) of the policy form separate clusters, which explains the dependence of classifier predictions on entities present in a sentence. Further, leaders of BJP form a separate cluster, which is closer (measured using cosine-similarity) to clusters of words like "anti-corruption", "cashless" which are associated to *Pro* stance concerning economic policies launched by BJP. To mitigate this dependence, we compare two methods of removing the named entities from the corpus before fine-tuning – remove these entities (black them out), or replace them with their named entity tags. From section 7, we find that fine-tuning results in better overall performance after replacing the named entities with their tags, since it preserves the grammar and structure of the sentence. The proposed model is hereinafter referred as **ID-RNN** (Ideology Detection - Recursive Neural Network).

7 Results

To account for class imbalance in the dataset, all the experiments are done on a balanced dataset by either undersampling the majority class or oversampling the minority class.

Table 4. Baseline Performance of Non-Neural Methods (**U**: Undersampling, **O**: Oversampling, **Acc**: Accuracy %, **F1**: F1-Score)

Models	**Step-1 (Stance Detection) Neutral vs Non-Neutral**				**Step-2 (Ideology Classification) Pro vs Anti**			
	Economic		**Technology**		**Economic**		**Technology**	
	U	**O**	**U**	**O**	**U**	**O**	**U**	**O**
	Acc% (F1)	**Acc% (F1)**	**Acc% (F1)**	**Acc% (F1)**	**Acc% (F1)**	**Acc% (F1)**	**Acc% (F1)**	**Acc% (F1)**
SVM	66.3 (0.63)	74.1 (0.61)	57.4 (0.50)	78.3 (0.54)	75.8 (0.74)	70.8 (0.65)	75.4 (0.66)	**86.4 (0.36)**
GB	62.6 (0.58)	65.4 (0.60)	40.8 (0.39)	61.9 (0.49)	68.3 (0.67)	67.5 (0.63)	74.2 (0.66)	79.1 (0.43)
DTs	59.8 (0.55)	69.3 (0.58)	45.8 (0.44)	66.7 (0.52)	65.1 (0.64)	67.8 (0.63)	68.1 (0.73)	74.8 (0.38)
RFs	65.9 (0.61)	**78.2 (0.63)**	41.8 (0.40)	**79.1 (0.52)**	**75.9 (0.74)**	**75.3 (0.68)**	76.4 (0.69)	85.8 (0.62)
Rocchio	68.1 (0.62)	69.7 (0.67)	**62.8 (0.56)**	78.1 (0.59)	71.7 (0.70)	70.7 (0.67)	74.3 (0.65)	84.2 (0.55)
kNN	52.9 (0.51)	66.5 (0.60)	43.8 (0.42)	72.4 (0.58)	71.2 (0.70)	60.8 (0.64)	56.8 (0.53)	58.6 (0.35)
NB	**70.3 (0.65)**	73.2 (0.65)	55.7 (0.48)	73.4 (0.61)	73.3 (0.72)	73.4 (0.70)	**78.3 (0.67)**	85.6 (0.45)
BoW	49.7 (0.49)	62.0 (0.58)	35.4 (0.35)	71.2 (0.56)	68.2 (0.67)	39.8 (0.33)	63.2 (0.58)	39.8 (0.30)

7.1 Baselines

We have developed strong baselines for both Step-1 (Stance Detection) and Step-2 (Ideology Classification) based on machine learning and deep learning models in order to draw a comparison with our proposed model.

- *Machine learning baselines:* We use the following machine learning algorithms as baselines: Linear SVMs, Gradient Boosting (GB), Decision Trees (DTs), Random Forests (RFs), Nearest Centroid (Rocchio), k-Nearest Neighbors Classification (kNN), Naive Bayes (NB), and Bag of Words (BoW). For each algorithm, we first create a vocabulary set on the training data and then convert the sentences into TF-IDF representation before classification. The best baseline for Step-2 (Ideology Classification) gives an

Table 5. Performance comparison of our model (**ID-RNN**) with DL baselines (**U**: Undersampling, **O**: Oversampling, **Acc**: Accuracy, **F1**: F1-Score)

Models	Step-1 (Stance Detection) Neutral vs Non-Neutral				Step-2 (Ideology Classification) Pro vs Anti			
	Economic		Technology		Economic		Technology	
	U	O	U	O	U	O	U	O
	Acc% (F1)	Acc% (F1)	Acc% (F1)	Acc% (F1)	Acc% (F1)	Acc% (F1)	Acc% (F1)	Acc% (F1)
DNN	70.2 (0.55)	75.3 (0.41)	68.4 (0.66)	75.6 (0.53)	75.1 (0.71)	74.5 (0.63)	74.8 (0.60)	86.3 (0.67)
RNN	74.4 (0.44)	74.5 (0.58)	77.8 (0.55)	77.5 (0.52)	72.4 (0.70)	74.2 (0.61)	79.0 (0.64)	84.5 (0.69)
CNN	70.7 (0.57)	77.3 (0.63)	84.1 (0.70)	83.3 (0.61)	74.2 (0.70)	75.0 (0.63)	83.3 (0.64)	87.9 (0.71)
RCNN	71.4 (0.65)	76.1 (0.64)	81.8 (0.71)	80.8 (0.57)	75.2 (0.72)	77.6 (0.74)	83.2 (0.65)	89.1 (0.78)
ID-RNN	**78.1 (0.75)**	**78.5 (0.77)**	**84.6 (0.80)**	**86.7 (0.90)**	**78.9 (0.79)**	**80.1 (0.81)**	**85.5 (0.82)**	**90.7 (0.93)**

accuracy of 75.3% (F1-Score - 0.70) for Economic Policies, and 86.4% (F1-Score - 0.36) for Technology Policies (with oversampling). The detailed results for these baselines for both the steps can be found in the table 4.

- *Deep Learning baselines:* Apart from a simple Deep Neural Network (DNN), we also experimented with the widely used Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs) [12] and Recurrent Convolutional Neural Networks (RCNNs) [14] as baselines. All these models are initialized with fine-tuned word2vec embeddings (except for DNN) and trained with 200 epochs using the Adam optimizer with a batch size of 32. In case of CNN, RNN and RCNN, we preprocess the dataset by first padding (append a <PAD> token) each sentence to the maximum sentence length of 59, and then, constructing a vocabulary index and mapping each word to an integer between 0 and 18,765 (the vocabulary size). Each sentence thus becomes a vector of integers. We now describe the architecture of these models briefly.
  - **DNN**: We use TF-IDF vectors as inputs to the DNN, which consists of 4 hidden layers with 512 nodes in each layer, with a 50% dropout following each dense layer.
  - **CNN**: CNNs, apart from computer vision, have also been applied to various NLP tasks [12]. The first layer uses low-dimensional word vectors as input in the CNN, while the next layer performs convolutions over these word vectors using multiple filter sizes. Next, we max-pool the result of the convolutional layer to form a one-dimensional feature vector, add dropout regularization (of 50%), and classify the result using a softmax layer.
  - **RNN**: RNNs can exhibit dynamic temporal behavior for a time sequence. This baseline model has 3 hidden layers with 256 GRU nodes in each layer and a recurrent dropout of 20%.
  - **RCNN**: RCNNs [14] combine RNN and CNN to exploit the advantages of both techniques simultaneously. We use 1D convolutions (with ReLU activation) and 1D max pooling to obtain a good representation. This is followed by 4 hidden layers of 256 LSTM nodes with a recurrent dropout of 25%. The output is finally classified using a softmax layer after passing through a fully connected layer.

  The results comparing the performance of our model with these baselines have been shown in table 5.

7.2 Proposed Model (ID-RNN)

In this section, we describe how using different word embeddings and training procedures affect the performance of our model. Here, we don't explain the details about the comparisons and experiments for Step-1 (Stance Detection), but primarily focus on Step-2 (Ideology Classification) that also has similar results. As described in Section 6, word2vec has been used with various modifications in our model: (a) G-W: Generic embeddings obtained after training word2vec on the Google News Corpus, (b) D-W: Embeddings obtained after fine-tuning on a collection of news articles about economic and technology policies, (c) D-W-NER: Fine-tuned embeddings obtained using the policy corpus after replacing the *Person* and *Organization* type of named entities with their named entity tags, and (d) D-W-BOE: Fine-tuned embeddings using the policy corpus, after removing entities.

Apart from using different types of embeddings, we also train the model using two methods: by allowing the input layer weights to train, and by keeping them frozen. For both the datasets, the minority class is oversampled to account for class imbalance. Initializing the embedding layer with D-W-NER, with a frozen embedding layer, gives the best results, with accuracies of 80.1% (F1-score - 0.81) for Economic policies, and 90.7% (F1-score - 0.93) for Technology policies. This is a significant improvement when compared to G-W with a trainable embedding layer, which gives accuracies of 65.8% (F1-score - 0.70) on Economic policies, and 76.2% (F1-score - 0.76) on Technology policies. This boost in performance is explained in section 6.2. The results demonstrating the

Table 6. Effect of different word vector initialization

Model	**Economic**		**Technology**	
	Accuracy	**F1**	**Accuracy**	**F1**
G-W	69.8%	0.76	80.2%	0.81
D-W	74.1%	0.79	84.8%	0.89
D-W-NER	**80.1%**	**0.81**	**90.7%**	**0.93**
D-W-BOE	71.6%	0.78	82.8%	0.71

Table 7. Effect of freezing embedding layer (**F**: frozen, **T**: trainable)

Model	**Economic**		**Technology**	
	Accuracy	**F1**	**Accuracy**	**F1**
G-W(F)	69.8%	0.76	80.2%	0.81
G-W(T)	65.8%	0.70	76.2%	0.76
D-W-NER(F)	**80.1%**	**0.81**	**90.7%**	**0.93**
D-W-NER(T)	73.7%	0.76	85.6%	0.88

effect of different word vector initializations and keeping the embedding layer trainable/non-trainable can be found in table 6 and table 7 respectively.

We also observe that using a cascading two-label classifier (Pro/Anti) rather than a three-label (Pro/Anti/Neutral) classifier provides better results, with the latter resulting in F1-scores of 0.69 and 0.84, as compared to 0.81 and 0.93 of the former on the economic and technology datasets, respectively.

8 Analysing Mass Media Bias

Several studies discuss how mass media is ideologically biased [27]. Sen et al. [25] show how the Indian mass media provides significant coverage to certain ideologies, rather than presenting a critical examination of policies. Budak et al. [6] talk about how the ideological bias in news organizations indirectly favors a particular side by criticizing the other side disproportionately. Our work is an improvement over the study by Sen et al. [25], in that it uses a more fine-tuned approach of stance detection, unlike the tool based sentiment analysis approach proposed in their work. Our work studies the ideological position of entities as well, alongside studying bias in media outlets. In this direction of analysing bias in the Indian mass media, we answer the following research questions in this section: (a) Which entities are most supportive or critical of the policies in the mass media? and (b) What is the ideological slant of media outlets regarding the economic and technology policies?

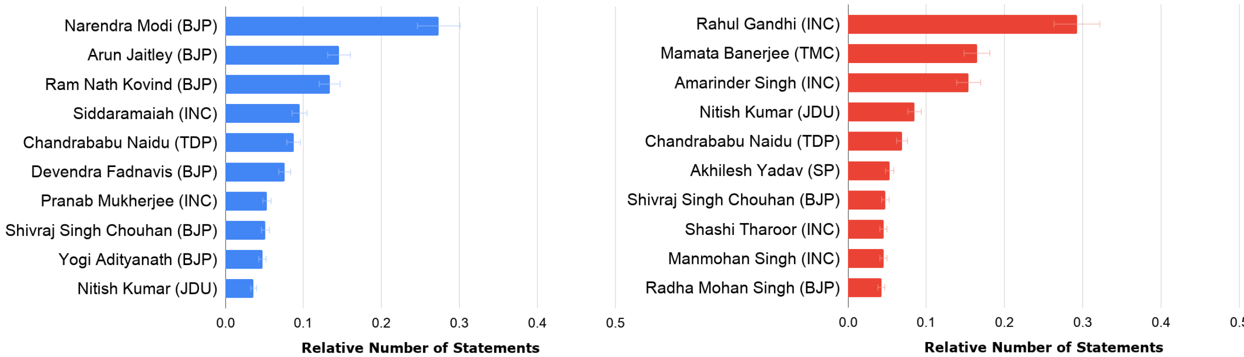
We have a significantly large dataset, and the models are trained only on an annotated subset of this dataset. The results and analysis in this section are presented after applying these trained models on the entire dataset.

8.1 Economic Policies

For this part, we consider our entire dataset of 5990 economic policy-related statements, out of which our model is trained only on 3855 annotated statements concerning four economic policies (350 Aadhaar, 1063 Demonetisation, 650 GST and 1792 Farmers' Protests). We filter out the neutral statements during the Step-1 (Stance Detection) of our classifier.

8.1.1 Ideological Position of Entities: We use our ideology detection model to get the count of *Pro* and *Anti* statements from every entity. These counts provide us the overall stance or position of an entity towards a policy. From this analysis, we find that most leaders of the currently ruling Bharatiya Janta Party (BJP) (like *Narendra Modi*, *Arun Jaitley*, etc.) are more pro-policy (figure 5a) than the opposition leaders (like *Rahul Gandhi* (INC), *Mamata Banerjee* (TMC), etc.), who are more critical of the economic policies (figure 5b). This is expected since most of these economic policies were formulated or implemented during the term of the ruling party (2014-19).

Our findings can also be corroborated by the statements that are made by these political leaders on the economic policies. For example, the prime minister *Narendra Modi*'s statement on Aadhaar enabled public distribution system (PDS),"*The government had detected 3.95-crore bogus ration cards, using technology and Aadhaar numbers to plug leakage in its social welfare programmes.*" shows his admiration towards the Aadhaar policy in detection of fake ration cards. On the other hand, the leader of opposition *Rahul Gandhi*'s statement on Aadhaar, "*For Congress, Aadhaar was an instrument of empowerment. For the BJP, Aadhaar is a tool of oppression and surveillance.*" is indicative of the opposition's criticism of the implementation of the policy by the ruling party (BJP). Similarly, we find the minister of finance *Arun Jaitley* making the statement, "*This is the positive impact of Demonetisation. More formalisation of economy, more money in the system, higher tax revenue, higher expenditure, higher growth after the first two quarters.*" in favour of Demonetisation. The leader of opposition *Mamata Banerjee* on the other hand made the statement, "*Demonetisation was not to combat black money. It was only to convert black money into white money for vested interests of the political party in power.*" indicative of her opposition towards the policy.



(a) Pro Entities for Economic Policies (b) Anti Entities for Economic Policies

Fig. 5. Top 10 Entities (in terms of Pro/Anti statements) for both Economic Domain; Political Affiliation is denoted by **(.)**

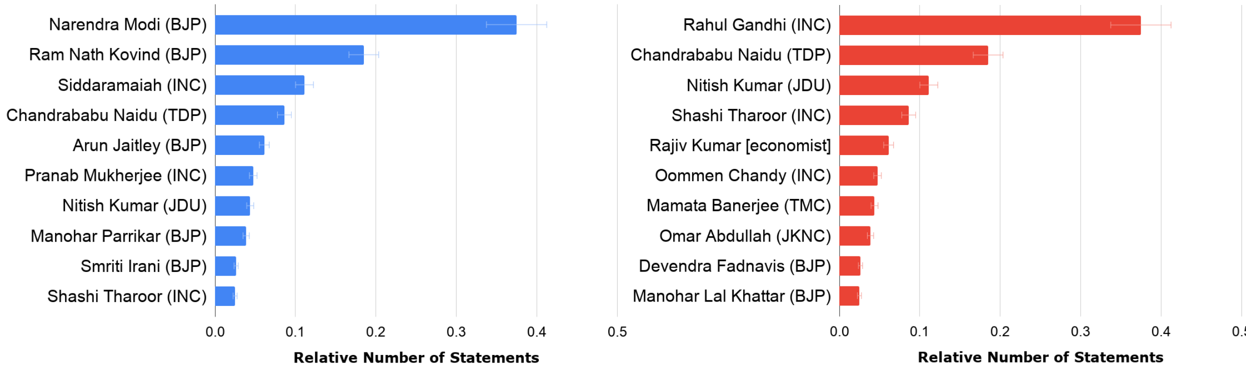
8.1.2 Ideological Slant of Mass Media: Table 9 shows the predicted distribution of statements in various mass media sources. We see that for each media source, the number of pro-statements far exceeds the number of anti-statements. We consider two independent samples as the count of pro and anti statements classified for each of the six media sources. We conduct an independent t-test with 1-tailed hypothesis to analyse the variability in the pro (M = 531.5, SD = 206.58) and anti (M = 202, SD = 76.14) samples. The test indicates ($t(10) = 2.22$, $p = .025$) that the media sources under consideration demonstrated statistically significant ($p < .05$) pro-policy coverage than anti-policy coverage.

8.2 Technology Policies

For technology-related statements, the analysis is done on 2252 statements (517 Aadhaar, 653 E-Governance, 691 Digital India, and 391 Cashless Payments), while we only have the annotations of 812 statements. We also examine the predictions qualitatively on the unseen dataset. A small subset of the predictions has been shown in table 8. For more detailed results, please refer to the supplementary material [4].

Table 8. Qualitative Analysis on the unseen technology-related dataset

Tech Policy	Pro	Anti
Aadhaar	Observing that at present, over 113 crore residents in India have Aadhaar, Prasad said that Aadhaar is safe, let me say proudly that the data is secure. I want to really emphasise that Aadhaar platform is the biggest anti-corruption platform in the world.	The software sometimes fails to read fingerprints and Aadhaar details of beneficiaries, forcing them to return without their monthly quota of subsidised foodgrain, Modi said. They are not only opposed to EVMs, they have problems with technology, digital transactions, Aadhaar, GST, BHIM app.
E-Gov.	As many as 73,000 villages will be brought into banking network with the help of technology, Pranab Mukherjee said, adding actions are being taken. Our government wants to use technology to curb dishonesty and bring transparency in governance.	In a series of tweets, Vijay Mallya said the PM advocates about the use of technology while the enforcement agencies don't take his words seriously and refuse to use technology. Modi said that the example of breaking, addition, and twisting of technology is being seen in the form of social media.
Digital India	In a fresh push towards digital payments, Modi on Thursday told businesses to shun cash and go digital to bring transparency and root out black money. Modi said that in this age, more than physical connectivity there is need for information highways.	Gandhi said not a single person has benefitted by the prime ministers promises of controlling inflation, depositing Rs 15 lakh in the accounts of each citizen and upgrading certain towns to smart city. Retired town planner Ram said: the challenge of achieving the target of getting selected for smart city category is colossal.
Cashless Payment	Advocating for cashless transactions, Modi has said that the large volumes of liquid cash are a big source of corruption and black money. This will improve the functioning of toll plazas, digital payments, Das said.	Quelling fears over security of digital transactions, Babu said that the SBI had left no stone unturned to ensure that the data of the users were not compromised. It is the same as encouraging cashless initiatives without creating infrastructure post-demonetisation and recalling old notes without calibrating ATMs, said Jamshedpur Petroleum Dealers' Association General Secretary.



(a) Pro Entities for Tech Policies (b) Anti Entities for Tech Policies

Fig. 6. Top 10 Entities (in terms of Pro/Anti statements) for Tech Domain; Political Affiliation is denoted by **(.)**

8.2.1 Ideological Position of Entities: A similar trend can be seen with the technology policies as well, where the leaders of the ruling party are found to favor technology strongly (figure 6a). For example, statements like these made by *Narendra Modi*, the Prime Minister of India, clearly indicate support towards a technology deterministic viewpoint: *"When poor farmers of villages have started adopting digital payments, now they (middlemen) have started spreading rumors."*. It is also noted that politicians of the ruling party are strong supporters of the technology policies rolled out by them. This statement made by *Ravi Shankar Prasad* on the Digital India policy clearly indicates the same: *"After coming to power, Prime Minister Narendra Modi gave the vision of Digital India as an important programme to transform India through the power of technology and bridge the digital divide."*. In contrast, leaders from the opposition parties (like *Rahul Gandhi* (INC), *Chandrababu Naidu* (TDP), etc.) are skeptical (figure 6b) of them. For example, the leader of the opposition, *Rahul Gandhi*, showed his skepticism towards the Digital India policy by making the statement: "*Digital India cannot become a euphemism for an Internet controlled by large remote corporations.*". Moreover, we see that the relative percentage of pro-technology statements is higher than the statements favoring the economic policies, which shows higher technology favoritism among policymakers.

This tendency of policymakers to propose technology as a solution to many problems has been studied in previous works as well. Pal et al. [24] show how in order to justify the policy move of Demonetisation, the Prime Minister increasingly emphasized on the usage of digital cash and payment wallets by invoking patriotism, technical advancement, and projecting cashless payment as a one-shot solution to the problems of people. In another study, Pal et al. [23] discuss how the current Prime Minister of India branded his image as a tech-savvy modernizer on social media and other platforms.

Table 9. Relative Pro/Anti Predicted Distribution in Media Sources

Newspaper Source	**Economic**		**Technology**	
	Pro (%)	**Anti (%)**	**Pro (%)**	**Anti (%)**
Deccan Herald	73.6	26.4	85.1	14.9
Hindustan Times	70.6	29.4	84.5	15.5
Indian Express	74.5	25.5	84.6	15.4
New Indian Express	68.1	31.9	80.0	20.0
The Times of India	68.2	31.8	86.3	13.7
Telegraph	70.0	30.0	81.9	18.1

8.2.2 Ideological Slant of Mass Media: Similar to economic policies, the media mostly covers statements that reflect technology-determinism (table 9). We conduct a similar t-test for pro-tech (M = 249, SD = 81.14) and anti-tech (M = 63.67, SD = 14.76) statements of these six media sources. The test indicates ($t(10) = 3.57$, $p = .025$) that the media sources under consideration demonstrated statistically significant ($p < .05$) coverage of tech-deterministic viewpoints as compared to the other side of the discourse. Additionally, these media sources seem to cover technology policies even more strongly than the economic policies (table 9). For each technology policy, the relative number of Pro, Anti and Neutral statements as covered by media are shown in Figure 7. It can be seen that as compared to other technology policies, more people are found to be neutral regarding the Cashless Payment technologies. Once again, most of our findings can be corroborated by earlier studies where the authors show how the

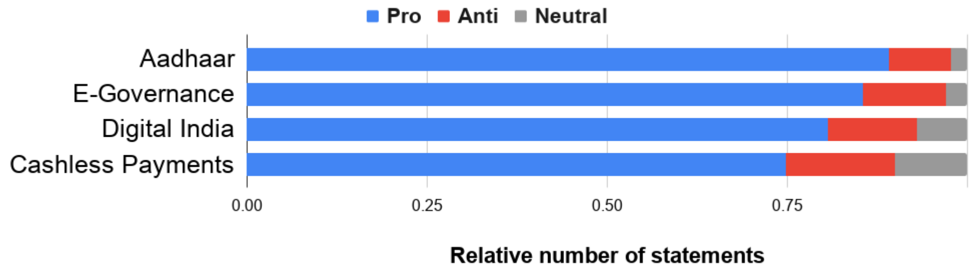


Fig. 7. Normalised distribution of the statements amongst technology policies as covered by media

Indian mass media is more keen on covering technology driven high-modernistic statements. For instance, Sen et al. [26] show how pro-technology aspects like *Development of Smart Cities* pertaining to the *Digital India* policy get a high coverage on mass media, while aspects that discuss the problems of the policy move get negligible coverage.

8.3 Generalizability

All the steps in our methodology until the model building stage are generic enough to be applied to any policy. The generalizability of our technology classifier model can be realized qualitatively from its performance on the 1440 unseen statements (table 8, more detailed in the supplementary [4]). To investigate the generalizability of the economic classifier, we trained our model on three policies and tested on a different policy. We achieve a test performance (on unseen policy) of 74.8% (F1-0.78) for Aadhaar, 70.7% (F1-0.72) for Demonetisation, 76.2% (F1-0.82) for GST and 65.8% (F1-0.72) for Farmers' Protests after training on the remaining three policies. Our model performs reasonably well in this set-up except for Farmers' Protests, which may be because it requires a significantly different domain knowledge from the other policies. A misclassified statement like *"By 2015, the farmers of Devanahalli, Kolar and Chikkaballapur will have to migrate elsewhere, says Shivanapura Ram, a farmer from Devanahalli."* needs the context of farmers' migration, which results from poverty and unemployment. Our experiments thus show that our classifiers generalize well on unseen data, unless the domain of a new policy is significantly different than others. We are currently trying to improve our approach's generalizability further.

We believe that our model can be further extended to determine the pro/anti stance of entire articles, in future. It also points towards the possibility of building a pro/anti government classifier, since the pro-policy statements generally show a high correlation with the pro-government ideology as the ruling members generally make them.

9 Conclusion

In this paper, we propose a framework to study the ideological biases existing in the Indian mass media, in terms of the statements covered by them on key economic and technology policies. We use an RNN based model to classify the statements made by influential elites on mass media into three classes of pro-policy, anti-policy, and neutral. Based on the coverage provided to these statements, we measure the ideological bias of different news-sources. Our findings indicate that the Indian news-sources generally cover the statements favoring the policies much more than those criticizing them, and take a pro-technology standpoint on technology policies. Our framework is generic enough to be applied to any other domain of ideology classification and presents a fine-tuned approach to detect the ideological position from policy discourse accurately. We believe that our framework and findings can serve towards pushing the Indian mass media towards greater self-regulation, enabling diversity in content publication, and educating the public about different viewpoints on key policies.

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