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Natural Language Processing (NLP)

What are the primary techniques and models used in NLP, and how have they evolved over the years?

There are 4 key eras of NLP: the rule-based, the probabilistic, the deep learning, and the transformer. Early computers scientist saw the potential of conversing with machines in natural language, with the concept of a computer even being capable of thinking hanging on this task (Turing 1950). : # How do these differ, and include some examples The early attempts in making computers interface with natural language were purely rule-based, with grammar and syntax being analysed through hard-coded rules (Johri et al. 2021). However, these models were fairly limited, as natural language will often fail to follow proper grammar, and even if it did, the number of rules will quickly become unmanageable, leading to the evolution of statistical models, which treated language as a probabilistic problem (Nadkarni, Ohno-Machado, and Chapman 2011). However, at a certain point, these probabilistic models became limited in their power due to the number of parameters needed to produce an accurate representation of natural language. To combat this, we used neural networks to analyse the language, with the Long Short-Term Memory models and Convolutional Neural Networks standing out as the state of the art in the field (Naseem et al. 2021). Finally, Vaswani et al. (2017) introduced the concept of transformers, which fixed the scalability issues found with LSTM and CNN models, while also allowing for context to travel from further distances. With the concept of transformers, Howard and Ruder (2018) showed how transfer learning can be used to fine-tune models to specific tasks, while using general pre-trained models, which greatly reduced the computational power required to create powerful models, as generalised base model weights could now be downloaded and tuned, rather than built from scratch.

What NLP tasks are linked with the concept of extracting framing?

The idea of extracting framing is a sub-task of sentiment analysis, where you take a piece of text and attempt to extract information about the author's feelings, opinion, or stance from this. Within the task of sentiment ansalysis, there are various well-defined sub-tasks, with one being highly correlated to framing detection being that of stance detection, where the stance of an author towards a topic is extracted from a piece of text (Küçük and Fazli 2020). However, stance detection is focused on a very simplified view of either seeing if a statement either supports or negates a secondary statement, which is overly simplistic if we are considering framing.

A task related to stance detection, but that does not necessarily share this issue is the task of perspective identification, where the perspective of the author, or more broadly their worldview, is determined through the text they produce. The fundamental task of this is determining membership of a group based on their writing (e.g. Palestinian vs Israeli), assuming that belonging to this group implies some level of shared belief (Lin et al. 2006). If one were to say that framing is formed through a set of beliefs, then the act of extracting framing would be highly correlated with the task of perspective identification.

A final related field is argument mining, where the argument being presented in a piece can be structured into a set of premises and conclusions (Lawrence and Reed 2020). Since framing ultimately aims to convince people to align with a certain worldview, it inherently has some form of argument structure. Extracting this structure, and the ultimate conclusion of the piece, whether that be stated or implied, could be a good proxy for extracting framing.

What are the current limitations of NLP in understanding nuanced language, such as sarcasm or implicit meanings, especially in the context of news media?

Fundamentally, modern natural language processing relies on the assumptions set out in structural linguistics, that is: language is static, probabilistic, and coherent (Arseniev-Koehler 2022). These assumptions are very prevalent in the groundbreaking work done by Mikolov et al. (2013), who embedded meaning from text simply by looking at words which share similar preceding and following words in a large dataset. This work, which is foundational to much of modern NLP, heavily relies on a static, probabilistic, and coherent language structure to produce results.

Although these assumptions are fine for creating a language model based on statistics, they do fail when looking at the upper limits of a model's ability to understand meaning and purpose. Lake and Murphy (2023) fundamentally disagree with the assumptions set out in structural linguistics and see language as a fluid, context-driven entity, where meaning is determined by factors external to the words themselves. For example, the sentence 'that ball is hard' obviously contains an observation, but the inherent meaning and purpose of that statement are lost without context. If this were at a football game, it may imply that the ball is too hard, painful to kick, or unfit for use, while if they were referring to a ball bearing, the statement could simply be an observation or a warning. One could argue that in a probabilistic model, these meanings are embedded simultaneously, but to have all meanings exist in a superposition means that they also do not exist in any meaningful way for analysis.

: # why is this fine? (line 1) Why are they fine in this context? Don't we want a model to actually give us an accurate analysis of the act of communication? : # It will be worth going back here into some of the foundaitonal news discourse literature - Fairclough, Gamson and Modigliani, Alan Bell, Roger Fowler,

This issue extends further when investigating figurative language, where common linguistic features such as sarcasm, irony, or metaphor have become an ongoing challenge for NLP researchers, with mixed results when attempting to identify them (Weitzel, Prati, and Aguiar 2016). This again highlights a problem with non-contextual text analysis, as even humans are resorting to self-tagging (#sarcasm, /s, or the use of italics) to indicate their use of sarcasm online (Kunneman et al. 2015), suggesting that even humans are struggling to understand figurative language in these context-free spaces.

Besides these issues with how language can be converted into a probabilistic model, there are also more practical issues with how powerful our models can be. Kaplan et al. (2020) showed that models follow a clear power law for loss, where model size, compute, and training data are the clear limiting parameters for how well an autoregressive model (all the LLMs) can perform. In this, there exists some entropy of language that even as these limiters grow, there will be some level of error in any language model.

What has been done looking specifically at media framing and NLP, or even in the climate space?

Numerous attempts have been made to leverage NLP to identifying framing, summarised as follows (as noted by Ali and Hassan (2022))

- Topic modelling
- Structural data modelling
- Hierarchical topic modelling
- Cluster analysis
- Neural network modelling
- Semantic modelling
- Word frequency modelling

Despite these efforts, many models encounter recurring issues that hinder their effectiveness compared to traditional social science framing analysis. The first issue is the oversimplification of framing in computational analyses, which often equate it to mere stances or opinions (Ali and Hassan 2022). The second issue is the misalignment with social science approaches, leading to a divergence between NLP and other framing analysis methodologies.

The first issue arises from the conventional NLP classification approach: labelling a dataset and training a model to identify patterns within those labels for predicting unseen examples. This process reduces the complexity of frames to a codebook, stripping away the nuances that define them. Moreover, creating more complex codebooks does not resolve this, as frames exist within spatial and temporal contexts (Vallejo, Baldwin, and Fremann 2024), which cannot be fully captured by text alone. Otmakhova, Khanehzar, and Fremann (2024) contend that most NLP methods fail to capture the ambivalence that distinguishes a frame from a simple stance or opinion, and this can only exist with an understanding of the existing frames in the shared consciousness of the readership.

The second issue highlights the superiority of modern neural networks in classification tasks compared to other models (Ali and Hassan 2022). The black-box nature of these networks prevents social scientists from understanding the reasoning behind frame classifications, as they cannot identify the features influencing these decisions, yet we continue to use them as they are far more powerful than more traditional, explainable models. Fremann et al. (2023) proposed a retrieval-based frame prediction method to address this, allowing for the isolation of sentences that significantly contribute to a frame at the document level. Additionally, concepts from argument mining may aid in extracting the structure of arguments and the premises that constitute a frame (Lawrence and Reed 2020).

Vallejo, Baldwin, and Fremann (2024) offers three recommendations for future research to address these challenges:

1. Incorporate non-textual, temporal features.
2. Consider dynamics across various documents and cultures.
3. Approach framing as a comparative task between documents.

What datasets already exist that could be useful?

Name	Source	Size	Label Type	Paper
News Argument Mining Corpus *	Editorials from Al Jazzera, Fox News and The Guardian	200 Articles	Argument Structure, with direction and premises	(Kiesel et al. 2015)
Frame Net	The British National Corpus	As of 2024, 13K word sentences, 200K sentences linked to 1200 semantic frames	A focus on roles and semantic meanings in words and sentences	(Baker, Fillmore, and Lowe 1998)

Name	Source	Size	Label Type	Paper
Media Frame Corpus	13 National Newspapers between 1990 and 2012	20K Articles	An issue (one of immigration, smoking, same sex marriage) and one or more of the 15 ‘cross-cutting’ framing dimensions	(Card et al. 2015)
Journal Editorials *	Editorials from Nature and Science about climate change	493 Editorials	One of Econ, Dev, Sec, Eth, Tech, Gov, Sci or Com, along with Urgency, policy or scale labels	(Hulme et al. 2018)
Cards	Climate contrarian Think Tanks and Blogs	25K Paragraphs	One of 80 climate-contrarian frames	(Coan et al. 2021)
Gun Violence Frame corpus	21 major US News Organisations	2991 Headlines	Alignment with one of the following frames: 1) Gun/2nd Amendment rights 2) Gun control/regulation 3) Politics 4) Mental health 5) School or public space safety 6) Race/ethnicity 7) Public opinion 8) Society/culture 9) Economic consequences	(Liu et al. 2019)
Heros and Villains *	Climate articles isolated from the NELA corpora (US and UK News)	248 Articles	Binary indicators for five frames: Resolution, Conflict, Human Interest, Moral, Economic. A group who the piece targets and one of hero, villain, victim; indicating the role that this group plays	(Fremmann et al. 2023)
Semeval 2023	Articles from google news from between 2020 and mid-2022	In English: 590 Articles	Genre: Opinion, objective, satirical. Frame: Same as MFC. Persuasion Techniques: Binary indicator for 23 different techniques that broadly fall into reputation attacks, justification, distraction, simplification, call and manipulative wording	(Piskorski et al. 2023)
Climate Fever	Claims from across the internet, supported with information sourced from Wikipedia	7675 claims with evidence from wikipaedia.	A claim evidence pair is then given a tag of ‘supports’, ‘refutes’, ‘not enough info’	(Diggelmann et al. 2020)
FLICC Dataset	Sentences selected from the Cards Dataset (Coan et al. 2021), plus some entries from addtitional datasets	2509 senetences	A falacy from the FLICC taxonomy	(Zanartu, Cook, et al. 2024)
AllSides	Articles selected from allsides.com	3564 Article Triplets	Stories adressing the same topic with a left, right and center tag forming a triplet	(Lee et al. 2022)

Name	Source	Size	Label Type	Paper
Nyt Frames *	NYT Articles	1.5 million articles	The 15 cross cutting frames from Boydstun et al. (2014)	(Kwak, An, and Ahn 2020)
NELA	RSS feeds from 361 different outlets throughout the course of the year, most current is 2022	1,778,361 articles	Labels the articles with the Media Bias Fact Check ratings	(Gruppi, Horne, and Adalı 2023) (Nørregaard, Horne, and Adalı 2019)

* There is no official name for the corpus

Climate Communication and Contrarianism

What are climate contrarian frames, and how have they been characterised in existing literature?

Climate contrarianism is a phenomenon born out of corporate-political campaigns that aim to downplay the impacts of climate change in order to protect profits. Notably, contrarians differ from skeptics, as skepticism is an important part of the scientific process where norms are challenged in the face of new information, whereas contrarians have a dogmatic belief that anthropogenic climate change is either not happening or not the existential issue that the scientific community believes it to be (Brisman 2012).

This contrarianism has manifested itself into ‘climate contrarian frames’ in the media, where contrarians have developed consistent tactics to sow doubt within the general public. Utilising the ‘unbiased’ nature of traditional news outlets, contrarians have been able to push their messaging through existing as the ‘counter’ to pro-climate scientists (Brisman 2012). While many news outlets are dismissive of these counterpoints (Brüggemann and Engesser 2017), mere exposure to these arguments is able to produce a reduction in trust in science and belief in anthropogenic climate change (McCright et al. 2016).

Broadly, climate contrarian frames callback to the concept that climate change is some form of left-wing hoax (Brisman 2012), being used to force a progressive agenda upon the population. From this, (Brisman 2012) found the three main contrarian arguments in US media to be: the criticism of climate science, the beneficial effects of climate change, and the threats that climate action will have on sovereignty and the economy. These concepts were further refined by Almiron et al. (2020), who defined four broad categories of contrarian arguments, those being: General scientific claims (The science is wrong, There’s no consensus), Specific scientific claims (It’s not happening, it’s not anthropogenic), Non-Scientific Claims (Criticism of individuals, Techno-fixes), and re-focusing of the issue (Economics, Political, etc.). Another attempt at creating a taxonomy of frames was done by Coan et al. (2021), who separated claims into: It’s not happening, It’s not us, It’s not that bad, Solutions won’t work, and The climate movement is unreliable.

Finally, Knupfer and Hoffmann (2024) created a taxonomy from German far-right digital networks, which found that the common frames were: Ideology, Totalitarianism, Insanity/Irrationality, Religion/Cult, Hysteria/Fearmongering, Hypocrisy/Moral superiority, Patronising FFF/Thunberg, Denialism, Costs.

A couple of themes have emerged from these characterisations of frames, most prominently the move away from denialist claims and towards attacks on the climate movement or on climate solutions (Coan et al. 2021), (Knupfer and Hoffmann 2024). It is also important to note that these taxonomies were all created in the scope of a codebook, but fall into the traps of oversimplifying framing as outlined by Vallejo, Baldwin, and Fremann (2024).

The only example of looking at roles I found was done by Fremann et al. (2023), who marked groups as either heroes, villains, or victims of the climate crisis. This take was unique amongst the others, which mainly aimed to create discrete classifications of arguments but could still show a lot of overlap. For example, the claim from Coan et al. (2021) that 'the climate movement is unreliable/corrupt' could be seen as the pair 'climate movement' and 'villain'. However, pairs possible such as 'Individuals' and 'villain' in the case of the personal responsibility argument seem to be exclusive to the codebook presented by Fremann et al. (2023).

There is also a case for investigating how climate change is now developing into a frame itself, where issues can be framed as 'climate-conscious', as seen in the media reporting on red meat (Sievert et al. 2022). This potentially places the counter view, in this case the 'vegan agenda', into the bucket of climate contrarian frames. This could possibly align with the actors' approach, whereby we see the vegans as the 'heroes' in the climate story.

How are climate change topics generally covered in the Australian news media?

In the 90s, Australia was seen as one of the leading nations in climate change awareness. However, due to political rhetoric and media influence, public opinion has been shaped to be more sceptical of climate change, putting it aside in the name of economic prosperity and making it more of a political issue (Taylor 2014). This concept is mirrored when looking at the reporting on climate change in our major outlets, where the most articles are written around the time major policy decisions and intergovernmental events, rather than extreme weather events (Schäfer, Ivanova, and Schmidt 2014), showing the media is more focused on the politics than the weather.

Various studies also found that the presentation of climate change is highly polarised and focused less on the impacts of climate change and more on the political discourse surrounding it. Altenkamp and McManus (2024) found that the discourse on the role of nuclear energy was dominated by the right-wing media (The Advertiser and the Daily Mail), who present it as a solution to climate change. It also reflects its critics as irrational. The presence of anti-nuclear rhetoric in papers was remarkably limited. Similarly, (Cowan, Dzidic, and Newnham 2023) found that the portrayal of youth advocacy for climate change is also highly polarised, with some framing the advocates as heroes and others as villains.

What is the current attitude towards climate change in Australia

A 2022 report splits climate attitudes into six categories: Alarmed, Concerned, Cautious, Disengaged, Doubtful, and Dismissive. Of these, they make up 31%, 27%, 23%, 2%, 9%, and 9% of the population respectively. 80% of Australians also report taking part in some form of climate action, with the most common being the actions which are cost-free (Richardson, Machin, and Williamson 2022).

A study of regional views of climate change also highlights the different stance rural communities have on climate change, with half of the respondents thinking their community is concerned, while the other half is skeptical, with the sceptical often focusing on the more day-to-day issues that they are facing (Buys, Miller, and Megen 2012).

In regard to attitudes on climate policy, Australians are very favourable towards government action on climate change, while also gently overestimating the role that coal and gas play in employment and economic prosperity, a common argument for why they should be kept open (Morison 2023).

Framing Studies

What is Framing?

The origin of framing as a concept for communications is often attributed to R. M. Entman (1993), who defined it as the act of *'selecting some aspects of a perceived reality and making them more salient in a communication text'*. Through this action, the frame can then: define problems, diagnose causes, make moral judgments, and suggest remedies.

: # Name some of the originals - e.g. Goffman. There's also some really interesting stuff around symbolic power of frames from people like JB Thomson etc that might be of use. Media and Modernity a nice little book. Goffman, E. (1974). Frame analysis: An essay on the organization of experience. Harvard University Press. Stuart Hall - primary definition Stanley Cohen

However, framing as a concept in psychology and sociology has existed before that, which both contributed to the concept of framing that R. M. Entman (1993) proposed. In linguistics, framing was initially investigated as a way to see how individual words can imply the existence and meaning of other words in the sentence. These 'semantic frames' are now highly documented (Baker, Fillmore, and Lowe 1998). These semantic frames also evolved into 'cognitive frames', which take terms and see what imagery and associations they inspire in the reader's mind. Meanwhile, in sociological research, frames were developed independently, leading to the origins of 'communicative frames', which look at the tools the writer can use to convey meaning, such as metaphor. These differ from cognitive frames as they introduce a new association in the reader's mind, rather than igniting an existing one. In modern work, these three types of frames are all analysed, often at the same time, under the term 'framing'; however, this often leads to disagreements and a lack of consistent definitions as to what constitutes a frame (Sullivan 2023).

> Semantic: The use of the word "killed" means that we expect a killer and victim to also exist.
>
> Cognitive: "John paid the waiter" evokes the concept of a bar or restaurant without explicitly stating that the restaurant exists.
>
> Communicative: "Trump killed thousands with COVID response"; the use of the word "killed" communicates a moral judgement on Trump and compares him to a murderer, even though Trump did not directly kill anyone.

These variations in framing definitions can also be described by analysing frames as either media frames or individual frames, with both being capable of being the independent or dependent variable in a framing analysis (Scheufele 2006). Following this train of thought, two broad types of framing emerge: one being equivalency framing, where a logically equivalent statement has different meanings caused by the reader's interpretation (75% lean vs 25% fat), and emphasis framing, whereby the media presents an issue in such a way that the 'subset of potential relevant considerations' that are emphasised are forefront in the reader's mind when constructing opinions (Druckman 2001)

How has framing been operationalised?

This lack of a unified definition has led many to try to define a simplified version of framing, treating it as a categorical task. This 'deductive' approach to framing analysis involves predefining frames as a set of features and then verifying their existence using a dataset. Whereas an 'inductive' approach seeks to work through a dataset and identify all the frames for a given issue, which is labour intensive and hard to replicate (Semetko and Valkenburg 2000).

This approach led Semetko and Valkenburg (2000) to produce the first set of generic frames that we widely agreed on, those being: human interest, conflict, responsibility, morality, and economic consequences. This concept of a set of pre-defined frames led to the creation of the commonly used 'policy frames codebook' (Boydstun et al. 2014). This codebook defines 14 universal frames that are found in media, such as economic, moral, and capacity. These frames, popularised by the creation of the Media Framing Corpus (Card et al. 2015), have become the de facto definition of framing in modern research.

These frames do somewhat reflect the original definition of framing. In the case of the economic frame, it highlights the economic aspects of an issue and makes them more 'salient' over the others. However, the isolation of these frames into categories fails to highlight the other features that were outlined by R. M. Entman (1993). To say that the excess government debt is caused by too many handouts is an economic framing of an issue, but blaming welfare recipients or corporate handouts presents a very different frame.

This has led some to develop hybrid systems for analysing frames, where a hybrid system of generic frames is combined with issue-specific frames. While this may be promising for bringing together the disconnected methods, it still leaves researchers drawing an arbitrarily line as to where to group together like ideas to form a frame (Brüggemann and Angelo 2018).

What are the impacts of framing

Framing, along with agenda setting and priming, constitutes a powerful set of tools that media organisations can utilise to influence public opinion and societal norms (R. M. Entman 2007). Within this landscape of media influence, conservative framing often becomes the dominant perspective, influenced by corporate advertisers and their substantial financial backing, which generally favours a more cohesive and unified presentation of conservative viewpoints (R. M. Entman 2007).

The effects of framing are multifaceted, splitting into frames that reside within the audience and those projected by the media (Scheufele 2006). These frames significantly impact how individuals interpret and understand issues. The effectiveness of framing depends heavily on the perceived credibility of the source by the audience (Druckman 2001). Initial perceptions of issues are shaped by framing; individuals are likely to reject a framing message only if they have been exposed to a conflicting frame previously (R. Entman, Matthes, and Pellicano 2009). As a result, framing enables societal elites and influential entities to effectively shape public opinion (R. Entman, Matthes, and Pellicano 2009). In times of crisis, actors strategically use framing to create narratives that help them retain power and justify existing policies, showcasing its role in maintaining influence and control over public perception (Hart Arjen Boin and McConnell 2009).

How do frames develop?

The process of developing frames can be roughly broken down into four stages: frame building, frame setting, individual-level framing, and feedback loops from audiences to journalists (Scheufele 2006).

Frame building, the action of defining what will be included in the frame, is primarily done by the journalists and news producers, who rely on their own attitudes and existing schemas (D'Angelo 2017). However, the level of journalistic autonomy these journalists have is questionable, since the power structures they exist in mean that they must appease those in power in their frame building process (Reese 2001). The decentralisation of media has also removed some of the journalists' role in defining the frame, as now individuals, businesses, and government organisations are able to undertake their own frame building processes (D'Angelo 2017) (Fielding 2024).

With the frame now developed, it can be set through the repeated exposure of the frame to the general public, whereby the exposure, assuming that the frame is acceptable, will be taken in and internalised (Fielding 2024). This is not a process that can be done individually, and instead relies on a network of communicators to present the frame (R. Entman, Matthes, and Pellicano 2009).

The uptake of a frame by the public then impacts the attitudes, beliefs, and behaviours of the public (Scheufele 2006). It is important to note that the public is not homogenous in their beliefs and therefore the uptake of frames will not be uniform. For example, individuals who identify as conservative are more likely to accept frames that cast doubt on the impacts of climate change (McCright et al. 2016).

The final step in the framing process is the feedback loop given from the public to the frame setters. This exists as journalists are also consumers of media and will therefore have their beliefs shaped by the previous frames they were exposed to. These schemas will then embed themselves in a positive feedback loop, further establishing the frame into the future (R. Entman, Matthes, and Pellicano 2009).

General Questions

What cool stuff have I come across so far?

Daume, Galaz, and Bjersér (2023) investigated the role of Twitter bots in bushfire discourse following the 2019 bushfires. They found that overall, climate change was very often linked to the bushfire discourse. The most common frames from these tweets were 'the political ideological struggle' and connection to extreme events, while 'damage and cost' was the most frequently retweeted. There was a higher interest in the tweets about the integrity of the online debate than there were in the contrarian claim tweets. Bots mainly participated in satire, humour, or parody.

Zanartu, Otmakhova, et al. (2024) developed a zero-shot method (able to create the output without any training examples) for creating fact-myth-fallacy-fact (Lewandowsky et al. 2020) using LLMs. This is a real step forward in creating meaningful interventions in the climate space.

Hamad et al. (2015) has performed deductive framing classification on the obesity crisis. What is cool is that the model was looking at blame attribution for the issue and found that it was pretty good at detecting this attribution.

Angus and O'Neill (2024) developed a low training data method for identifying contrarian frames by examining the logistic probabilities of an article being produced based on a set of stances. Although this only considers contrarianism in a -1 to 1 style of classification, the methods for generating data and performing the analysis could be useful.

Lee et al. (2022) developed a task called Neutral Multi News Generation (NEUS) which focuses on generating unbiased summaries by combining multiple biased texts. This also provides a dataset of articles that take different frames on the issue and an expert summary of the issue and the points covered.:

What outputs are needed from this automated analysis to produce meaningful interventions against CCFs?

Interventions against contrarian frames have not been extensively researched; however, there should be a large overlap with the writing on misinformation interventions, which have been broadly covered.

The framework for systematically combating misinformation, developed by (Cook 2024), splits the task of combating climate misinformation into four sequential tasks: detecting the misinformation, deconstructing the arguments, debunking the arguments, and deploying this debunking information where it is needed. This is seen as the most psychologically effective way to combat misinformation, as it is difficult to dislodge from people's minds due to various effects (Lewandowsky et al. 2020).

Considering this task as the detect stage of the framework, the outputs would need to be granular enough to allow for someone to deconstruct the argument and why it may be misleading.

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