**2 Literature Review**

This section gives an overview of previous work on methods to detect political stance in text, to generate alternative legislation, and on decision-making in the European Parliament.

**2.1 Detecting political stance in text**

Scholars have tried to predict and model politicians’ positions on policies long before the rise of large language models. Based on the idea that political preferences can be modelled in a d-dimensional space with Euclidean distances, Enelow and Hinichs have laid the groundwork for modelling the relation between political actors and policy positions (Enelow & Hinich, 1989). They hypothesize that politicians or candidates chose their position on certain issues in the Euclidean space and that voters can make their decision by assessing the distance of the candidate’s point in space and their own position (Enelow & Hinich, 1989). Those positions are called ideal points, indicating that a bill with the same political direction would be in perfect alignment with the candidate or legislator (Gerrish & Blei, 2011).

The theory can be applied using roll call votes to model the legislators’ positions, e.g. with the NOMINATE geometric scaling method by Rosenthal (Rosenthal & Poole, 1997). Using NOMINATE, Hix and Noury mapped the positions of party groups in the European Parliament and found the right-left dimension to be the most defining and consistent feature to distinguish party positions (Hix & Noury, 2009).

The ideal point model or spatial theory has been developed further to tackle the problem of increasing parameters and to counter questions of statistical validity (J. Clinton et al., 2004). Jackman and Clinton made fundamental contributions by using Bayesian models, Markov chain Monte Carlo methods in particular, on roll call data of the US Senate (J. Clinton et al., 2004; J. D. Clinton & Meirowitz, 2001; Jackman, 2001). Londregan achieved to decrease the parameters to be estimated with the ideal point model using classic maximum likelihood estimation on roll call votes of the Chilean Senate committees (Londregan, 2000).

The above approaches are able to explain e.g. how changing the ideal point affects the policy’s support via the used coefficients and allows to infer the positions of policies of legislators (Jackman, 2001). However, they lack the ability to predict legislators’ positions on a future bill. Gerrish and Blei point out that for predictions, additional data other than the pure votes are needed. Using supervised topic modelling of bills in addition to the ideal point model, they not only add a machine learning method to the area but also achieve high accuracy in predicting the US House of Representatives’ and Senate’s votes (Gerrish & Blei, 2011).

In the realm of machine learning methods, not only the performance of random forests, decision trees, and linear regression as classifiers of polarisation in tweets has been researched (Hajare et al., 2021) but also the use of Recurrent Neural Networks (RNN) to detect ideological bias in US Congress debates. Based on the idea that RNNs have the advantage of capturing semantic context, Iyyer shows that they outperform bag of word models on the task of distinguishing the political positions (Iyyer et al., 2014).

Many methods used to detect political direction in legislative texts originate from the classic research question in political science of how to locate parties on different policy dimensions based on text (Benoit et al., 2016). The Manifesto research project shaped the field with the canonical database of parties’ manifestos and their policy positions labelled by expert annotators (Volkens et al., 2013). Different from this annotator-centred approach, Benoit and Laver analyse party manifestos of the UK by focusing on the words as data and word frequency only. Similarly, Peterson and Spirling show on the basis of a simple bag of words model that accuracy can be used as an indicator for political polarization in parliamentary speeches (Peterson & Spirling, 2018). While these analyses are vital to the field, this thesis focuses on the analysis of legislative texts as a subtopic of political stance detection in texts in general.

Lastly, stance analysis should be differentiated from the similar sentiment analysis. The active field of sentiment analysis usually determines whether a text expresses a positive, negative, or neutral opinion, either in general or towards a topic, while stance detection analyses more openly the position towards a predefined topic of interest (Mohammad et al., 2016). However, overlap exists and brings fruitful insights, especially with the use of LLMs.

**2.1.2 Using LLMs for political stance detection**

Large Language Models have shown unknown and outstanding capabilities in various Natural Language Processing tasks, including classification tasks that used to be done with rule-based models (Brown und andere Quelle zu classificain?). Existing research has explored two main capabilities of LLMs that can be exploited for the classification task of (political) stance detection and that differentiate them from previous methods: the vast amount of data which LLMs have been trained on, and the possibility to optimise LLMs on specific down-stream tasks.

First, based on their high-dimensional representation of words or tokens, LLMs have shown to be capable of processing words in context in an unseen manner and up to the level of high linguistic standards (Petersen & Potts, 2023). This is crucial for stance detection, “as stances are often implicitly embedded rather than explicitly stated in the text” (Lan et al., 2024). Wu et al. used this embedded knowledge of LLMs when estimating policy positions of politicians on gun control and abortion rights. Their research supports the hypothesis that LLMs can draw from their training data when the given information in the prompt is insufficient for an estimation, in this case how a given politician’s stance is on the two topics (Wu et al., 2023).

Second, extensive research has been done on performance improvement of LLMs and ChatGPT in particular, with fine-tuning, see Ouyang et al. (2022) for a ground laying study. Unsurprisingly, ChatGPT’s success lies in its high performance in zero-shot learning, where only a description of a task without explicit prior training on that task is sufficient to achieve good results (Brown et al., 2020; Kim et al., 2021). However, a wide field of scholars has shown the improved performance fine-tuning can bring to LLMs in general and ChatGPT in particular to perform a diverse set of tasks (Alt et al., 2019; Gao et al., 2021; Lu et al., 2022; Schick & Schütze, 2021b, 2021a; Shi & Lipani, 2023).

Fine-tuning as one of multiple possibilities to specialise LLMs on down-stream tasks has been widely used for sentiment analysis (Mohammad et al., 2016; Singh & Srivastava, 2023). Fewer studies examine the method of fine-tuning to detect political stance in text, e.g. Gül et al. observe substantially improved accuracy of stance detection with various fine-tuned LLMs (Gül et al., 2024). Other authors find performance gains with fine-tuned models when classifying tweets of candidates in the U.S. Congressional elections (Heseltine & Clemm von Hohenberg, 2024). Lan et al. support the potential of fine-tuning when highlighting that without domain-specific knowledge, LLMs often fail to meet non-LLM baselines in stance detection (Lan et al., 2024). Waldon et al. tried to few-shot prompt the LLM text-davinci-003 to predict the consensus that humans might come to when interpreting a legal document. While finding better results than with zero-shot prompting, they propose to use fine-tuning methods to improve the predictions (Waldon et al., 2023). With a combination of fine-tuning and reward models, Bakker et el. have crucially advanced the field in showing that LLMs can not only recognize different political positions in text but also find and generate consensus among them (Bakker et al., 2022).

Enelow and Hinichs highlight that the measurement of candidates’, voters’, and policy positions includes error and uncertainty because of unobserved confounders. Voters and candidates are caught in a field of tension, when candidates decide on their positions with the motivation to maximise voter’s approval and have to possibly negotiate internally (Enelow & Hinich, 1989). Errors in previous annotator-centred methods can also result from measurement error of the annotators; a known critique to the Manifesto Project dataset (Meyer & Jenny, 2013). Using LLMs poses an innovative approach, as LLMs might be able to assess political direction of texts while including the uncertainty that is inherent to the language of legal texts.

**2.1.2 Using LLMs to alter political stance**

Changing political bias in texts is a challenging task that requires precise understanding of the location and meaning of the political expression and domain-specific knowledge. LLMs might exhibit competency here but few studies have tested LLMs’ capabilities on the task. Chen et al. trained an autoencoder to flip political bias of news headlines, while Schlicht et al. tested the ability of various LLMs of OpenAI to debias political bias in news (Chen et al., 2018; Schlicht et al., 2024). This research can be placed in the realm of “controlled generation”, where the aim is to “rewrite a text with a given attribute” (Chen et al., 2018; Guu et al., 2018; Hu et al., 2018). There is a research gap to systematically identify and evaluate the use of LLMs to alter political stance in text.

**2.3 Decision-making in the European Parliament**

The EP’s decision-making is the result of an agreement of 705[[1]](#footnote-1) elected members from twenty-seven member states. MEPs coalesce in supra-national party groups or attend the plenary as non-attached members. MEPs are not obliged to join a group based on their national party affiliation - creating multinational cooperation in political groups is explicitly encouraged, e.g. by alphabetical seating order in the plenum as opposed to seating based on nationality (European Parliament, n.d.-b). Scholars have widely researched how international cooperation is realised among political groups (Hix et al., n.d.; Kelleher, 2002; Kreppel, 2002). Even after enlargements of the EU and the joining of new national parties, a left-right ideology dominates national identity (Hix, 2002; Hix & Noury, 2009; Meyerrose, 2018; Spirling & McLean, 2007).

The EP’s size not only makes it one of the largest parliaments globally but also an interesting example for the theory of finding consensus among a large group of individuals with diverse preferences (C.-C. Li et al., 2019). Voting in the EP follows some patterns of voting in international organisations (IO): Just as IO tend to vote via majority rule rather than unanimity, with the ordinary legislative procedure (COD) legislation is adopted with a simple majority (TFEU, 2008). In only very few cases do MEPs support a law with consensus, eight bills between 2009 and 2022 received no votes against. Here consensus is defined as the absence of opposition, following the widely accepted definition of Schermers (Schermers, 2011). Apart from this typical aspect of deicion-making in IOs, three main characteristics of the EP’s decision-making make it a unique setting for the process of finding consensus.

First, in each legislative period, the EP decides on many procedures and usually, it adopts the proposed legislation. Only counting the laws of the COD procedure, the members of the European Parliament (MEPs) voted on 6,418 legal procedures and 2,392 budget decisions between 2009 and 2022, both of which are part of 30,672 total votes including non-legal procedures in the same time. The 6,418 legal COD procedures include decisions on changing of laws and 1,393 final proposed laws. In the thirteen analysed years, only twenty-eight of those laws were rejected by the EP, which makes 97.99% of laws to be adopted.[[2]](#footnote-2)

Different from other legislative procedures such as the consultation procedure, the COD allows to observe the EP’s decision-making most independently from other institutions’ political agenda. The COD is the general procedure of passing laws in the European Union and is initiated by a legislative proposal of the European Commission. The EP can then amend the proposal to its discretion (EU Monitor, n.d.). Different from the consultation procedure where the EP might tend to propose only amendments that are likely to be accepted by the Commission, the COD allows for the most effective agenda-setting of the European Parliament.

Second, with the precaution that the EP is not a national parliament, it resembles the parliament of consensus democracies, as defined by Lijphart. Other than majority democracies, where bare-majority decisions are enabled by a government-vs-opposition pattern, consensus democracies favour large majorities and broad coalitions (Lijphart, 1984). This is shown in the EP: Not only do the MEPs usually agree to vote in favour of a law, most of the time they do so with an overwhelming majority. 50% of all proposed laws between 2009 and 2022 have been decided on with an agreeing majority of over 70% of all MEPs present on the day of the plenary sitting (see table 1 in annex for detailed thresholds). Attendance rate of MEPs is high with 85.78%, 89.85%, and 96.97% in the periods of 2009-2014, 2014-2019, and 2019 to 2022, respectively.[[3]](#footnote-3)

Third, there have been and there are increasingly more veto players in the European Parliament. Veto players as defined by Tsebelis, are political actors whose consent is necessary to change the status quo (Tsebelis, 1995). The party composition of the EP has not changed drastically in the past 25 years but following three trends. Since the EP’s founding in 1979, the party groups of Social Democrats (S&D[[4]](#footnote-4)) and of Christian Democrats (EPP[[5]](#footnote-5)) make up the two biggest shares of a composition that has further always included left-wing, right-wing, and liberal groups. Throughout the years, multiple Eurosceptic and a Green group arose and on average, increased their share. Overall, the right-wing party groups gained support - with now three right-wing party groups after the 2024 election - and the two major party groups S&D and EPP increasingly lost voters. See the composition of the legislative period of 2019 to 2024 in figure xy. The steady loss of seats of S&D and EPP distributes the veto power among the party groups increasingly evenly. As Tsebelis finds, the more politically diverse veto players, the less likely is a policy change away from the status quo (Tsebelis, 1995).

Ein Bild, das Screenshot, Text, Diagramm, Kreis enthält.

Automatisch generierte Beschreibung

Figure 1: Party Groups of the European Parliament 2019-2024, constitutive session (European Parliament, 2024c)

**2.3.1 Shaping legislation via amendments**

The above characteristics can be explained with the fact that the EP had been lacking the right to propose a law until its competencies were enhanced with the Treaty of Lisbon in 2009 and only received a right of initiative in very few cases since (European Parliament. Directorate General for Internal Policies of the Union. et al., 2020). Within the COD procedure, a legislative proposal must be initiated by the Commission and is then passed to the EP, which can amend the proposal to its discretion. This gives the MEPs more influence over the purpose or application of a law by amending it than by just rejecting the proposal. Kreppel highlights that amendments of the EP make a substantive contribution to the legislative process in the EU (Kreppel, 2002).

Amendments can consist of the suggestion to delete, add or replace a single word or a whole paragraph of the Commission’s proposal and in consequence, they vary greatly in length and significance. Some amendments address rather technical aspects of legislation, some address the political direction of the content, or the amount of budget associated with it, some constitute a softer change of voice and only alter the recital.

Amendments are diverse in political direction and cause strong disagreement – 2252 out of 5025 amendments have been rejected between 2009 and 2022, constituting a rejection rate of 44.82%.[[6]](#footnote-6) This underlines that the EP is far from being only a “chamber of debate” (Kelleher, 2002) and that MEPs have clearly opposing political preferences which they express.

**2.3.2 Roll call votes as only one way of voting**

The usual way to vote in plenary sessions is by show of hands, where the party group’s leaders sit in the first row of the plenum and indicate the group’s preference by a thumbs up or down to their fellow group members. Members are free to follow the preference of their group leader by raising or not raising their hand or they might vote diverging from the group’s preference. Electronic vote can be requested by the Parliament’s President if the show of hands might be unclear (European Parliament, n.d.-a). In both ways, only the sums of votes in favour, against or abstaining are recorded but not the votes of individual MEPs or political groups. This is due to the high frequency of multiple votes being cast in plenary weeks, sometimes up to ten per minute. However, party groups or groups of at least 38 MEPs can request so called roll call votes (RCV) prior to the plenary sessions for which the voting decision of each MEP is recorded and published on the Parliament’s websites[[7]](#footnote-7) (European Parliament, n.d.-a). Roll call votes constitute the main share of votes cast and build a good representation of the topics voted on in each legislative period. They are further the typical type of data to analyse in political stance detection and testing methods on RCV builds on a strong literature background (J. Clinton et al., 2004; Gerrish & Blei, 2011; Highton & Rocca, 2005; Hix & Doru, 2024; Jackman, 2001; Rosenthal & Poole, 1997).

1. In the legislative period of 2024-2029. Number of members have been changing due to the joining or leaving of countries but have been set to a maximum of 751 seats. [↑](#footnote-ref-1)
2. Own analysis of dataset of Simon Hix. [↑](#footnote-ref-2)
3. Own analysis of dataset of Simon Hix. [↑](#footnote-ref-3)
4. Short for “Group of the Progressive Alliance of Socialists and Democrats in the European Parliament” [↑](#footnote-ref-4)
5. Short for “Group of the European People's Party (Christian Democrats)” [↑](#footnote-ref-5)
6. Own analysis of dataset of Simon Hix. [↑](#footnote-ref-6)
7. See e.g. the results of all votes on 21 November 2023 in Strasbourg here: <https://www.europarl.europa.eu/doceo/document/PV-9-2023-11-21-VOT_EN.html> [↑](#footnote-ref-7)