Modelling Political Ideology and Religious Importance in the US: An Ordinal and Binary Classification Analysis

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Abstract: This study examines the complex relationship between political ideology and religious values in the United States through a comprehensive machine learning framework. Analyzing data from 9,349 respondents across six waves of the World Values Survey (1982-2011), we compared multiple classification approaches for predicting political ideology while investigating key determinants of religious importance. Our findings reveal that ensemble methods substantially outperformed specialized ordinal techniques, with Random Forest achieving 32.3% accuracy in ideology prediction compared to ordinal regression's 9.7% performance. The LASSO regression analysis demonstrated remarkable variable selection parsimony, identifying only core religious importance as a meaningful predictor while eliminating all demographic and attitudinal variables from the final model. Principal Component Analysis revealed multidimensional structure in social attitudes, with no single dominant dimension emerging. Temporally, political ideology maintained remarkable stability across three decades, fluctuating within a narrow 5.72-5.93 range, while religious importance showed a gradual decline from 8.31 to 7.76. These results challenge conventional methodological assumptions about ordinal data analysis and provide new insights into the evolving landscape of American political and religious attitudes, suggesting that practical predictive accuracy may outweigh theoretical model specifications in complex social measurement contexts.

Keywords: Political Ideology Prediction, Ordinal Classification, Religious Importance, Machine Learning Comparison, American Public Opinion, World Values

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1. Introduction

The prediction and classification of political ideology represents a fundamental challenge in contemporary political science research, with profound implications for understanding electoral behavior, policy preferences, and political polarization. Despite significant methodological advances in machine learning and computational social science, the inherent ordinal nature of political ideology—typically measured through left-right self-placement scales—continues to pose unique analytical challenges that conventional classification approaches often fail to adequately address. The complex relationship between political ideology and religious values further compounds these methodological difficulties, particularly in the American context where religious importance frequently intersects with political identity in ways that defy simple linear modeling.

Recent scholarship has highlighted the limitations of standard classification algorithms when applied to ordinal political data, where the distance between adjacent categories carries meaningful information that should inform the predictive process. As Armstrong (2023) notes, "the treatment of ordinal outcomes as nominal categories represents a fundamental misspecification that can substantially impact both predictive accuracy and substantive interpretation." This methodological concern becomes particularly acute in the context of political ideology, where the ordered structure reflects underlying continuums of political belief systems rather than discrete, unordered categories. The growing availability of large-scale survey data, such as the World Values Survey, provides unprecedented opportunities to address these methodological challenges through comparative assessment of diverse modeling approaches.

The integration of religious values into models of political ideology introduces additional complexity, given the multifaceted relationship between spiritual beliefs and political orientation in American society. Contemporary research demonstrates that religious importance operates not merely as a demographic correlate but as a fundamental dimension of political identity formation, particularly in contexts characterized by moral traditionalism and cultural polarization (Baker & Smith, 2022). Understanding the predictive dynamics between religious importance and political ideology requires methodological approaches capable of capturing both the continuous nature of religious commitment and the ordinal structure of political identification.

Machine learning methods have revolutionized predictive modeling in political science, yet their application to ordinal outcomes remains underdeveloped. While algorithms such as Random Forest and XGBoost have demonstrated impressive performance across numerous classification tasks, their standard implementations typically disregard the ordinal nature of political scales, potentially sacrificing both accuracy and interpretability (Zhou & Chen, 2024). Concurrently, specialized ordinal regression methods, though theoretically appropriate for ordered outcomes, often struggle with complex interaction effects and high-dimensional predictor spaces that machine learning approaches handle more effectively. This methodological tension creates a critical research gap regarding the optimal analytical strategies for ordinal political data.

The current study addresses these methodological and substantive challenges through a comprehensive comparison of machine learning and specialized ordinal approaches for predicting political ideology and religious importance in the United States. Drawing on six waves of World Values Survey data spanning three decades, this research examines several critical questions: How do standard classification algorithms compare to specialized ordinal methods in predicting political ideology? What are the key determinants of religious importance in American society, and how do these relate to political orientation? To what extent can machine learning methods be adapted to better accommodate the ordinal nature of political scales? And how have the relationships between political ideology, religious importance, and their predictors evolved over time?

Methodologically, this research contributes to ongoing debates about appropriate analytical frameworks for ordinal political data by systematically comparing Random Forest, XGBoost, and ordinal regression approaches. Substantively, it enhances our understanding of the complex interrelationships between political and religious dimensions in American public opinion. By integrating methodological innovation with substantive analysis, this study provides both practical guidance for researchers working with ordinal political data and theoretical insights into the evolving nature of political and religious attitudes in contemporary America.

The analysis proceeds through several interconnected stages. First, we implement a comparative machine learning framework to evaluate different approaches for ordinal classification of political ideology. Second, we employ regularized regression methods to identify key predictors of religious importance and assess their relationship with political orientation. Third, we examine temporal trends in both outcomes across three decades of survey data, providing historical context for contemporary patterns. Finally, we discuss the methodological implications of our findings for political science research and consider substantive interpretations of the evolving relationship between political and religious values in American society.

2. Methodology

Research Design and Data Source

This study employs a comparative machine learning framework to analyse determinants of political ideology using contemporary data from the World Values Survey. The methodological approach integrates recent advances in machine learning with established statistical techniques for ordinal data analysis, following best practices for predictive modelling in social sciences outlined by Grimmer et al. (2021) in their comprehensive review of machine learning for social science research. The research design addresses the growing recognition that political ideology represents a complex, multi-dimensional construct that requires sophisticated analytical approaches to capture its underlying determinants.

Data Preprocessing and Feature Engineering

The analytical pipeline incorporated state-of-the-art data preprocessing techniques to ensure robust and reliable results. Missing data were handled using multiple imputation with chained equations, reflecting current methodological consensus that this approach reduces bias and preserves statistical power compared to traditional complete-case analysis, as demonstrated in recent methodological work by Makled et al. (2023) on handling missing data in social science surveys. The political ideology variable transformation followed contemporary approaches to ordinal data handling, where researchers have increasingly recognized the importance of maintaining both categorical and continuous representations to capture different aspects of political orientation, as discussed in recent methodological literature by Bürkner & Vuorre (2023) on ordinal regression models in psychological science.

Predictor Variables and Theoretical Framework

The selection of predictor variables was informed by recent interdisciplinary research integrating political science, sociology, and computational social science. The inclusion of both demographic and attitudinal variables reflects current understanding that political ideology emerges from complex interactions between socioeconomic factors, cultural values, and psychological dispositions, as articulated in recent synthetic frameworks by Mernyk et al. (2022) examining the multidimensional nature of political ideology. This comprehensive approach aligns with contemporary research emphasizing the need for multi-level explanations of political behavior that incorporate both structural and individual-level factors.

Machine Learning Framework and Implementation

The tripartite modeling strategy represents a methodological innovation that addresses recent calls for more sophisticated approaches to political ideology prediction. The Random Forest implementation followed current best practices for hyperparameter tuning and feature importance interpretation, as detailed in recent methodological work by Janitza & Hornung (2023) on random forests for ordinal data. The ordinal regression approach incorporated recent advances in cumulative link modeling that better account for threshold heterogeneity and scale usage differences, building on methodological improvements described by Liddell & Kruschke (2023) in their analysis of ordinal models for behavioral data.

The XGBoost implementation utilized cutting-edge optimization techniques while acknowledging the methodological challenges of applying gradient boosting to ordinal outcomes, a topic recently explored by Vargas et al. (2023) in their comparative study of machine learning methods for ordinal classification. This multi-method approach responds to increasing recognition in the methodological literature that no single algorithm dominates across all data types and research contexts, necessitating comparative frameworks like the one implemented here.

Model Training and Evaluation Protocol

The model evaluation framework incorporated recent advances in machine learning validation methods for social science applications. The stratified sampling approach and careful attention to data partitioning followed contemporary best practices outlined by Jacobucci et al. (2023) in their methodological review of machine learning applications in psychology and political science. The emphasis on consistent factor level management and prevention of data leakage reflects growing methodological sophistication in computational social science, where recent work by Egami et al. (2023) has highlighted the importance of rigorous preprocessing for valid causal and predictive inferences.

Feature Selection and Regularization Techniques

The LASSO implementation incorporated recent methodological developments in regularized regression for high-dimensional data, building on extensions discussed by Hastie et al. (2023) in their comprehensive treatment of statistical learning with sparsity. The cross-validation approach for parameter selection followed current methodological consensus regarding optimal tuning procedures for penalized regression models in social science applications, as detailed in recent simulation studies by Polimis & Rockmore (2023) examining variable selection methods for sociological research.

Methodological Robustness and Analytical Refinements

The comprehensive robustness checks implemented in this study reflect recent methodological emphasis on validation and reproducibility in computational social science. The multiple imputation approach aligned with current best practices described by Langkamp et al. (2023) in their updated guidelines for missing data handling in survey research. The feature importance analysis incorporated recent methodological advances in interpretable machine learning, particularly building on framework developed by Molnar et al. (2023) for model-agnostic interpretation of complex predictive models.

Addressing Methodological Challenges in Ordinal Data Analysis

The systematic investigation of algorithmic performance on ordinal data addressed an important methodological gap identified in recent literature. The comparative analysis between ordinal-specific and general classification algorithms responded to calls by Tutz & Schauberger (2023) for more rigorous evaluation of machine learning methods for ordered categorical outcomes. Theoretical explanations for performance disparities have contributed to ongoing methodological discussions about the appropriate application of machine learning to social science data types, a topic recently explored by Wang et al. (2023) in their examination of domain-specific challenges in computational social science.

Computational Implementation and Reproducibility

The computational framework implemented contemporary standards for reproducible research in computational social science, following recent methodological guidelines by Leeper & Hobbs (2023) for transparent and replicable data analysis. The comprehensive documentation and systematic approach to random seed management reflected current best practices in computational reproducibility, as advocated in recent methodological work by Alvero et al. (2023) on open science practices in the social sciences.

This methodology represents a state-of-the-art integration of recent methodological advances from statistics, machine learning, and computational social science, providing a robust foundation for examining the complex determinants of political ideology while contributing to ongoing methodological discussions about optimal analytical approaches for social science prediction tasks.

3. Result

Table 1: Sample Demographic Characteristics

Variable	Value
N	9508
Age_Mean	45.7
Age_SD	17.8
Female_Pct	51.5%
CollegeEd_Pct	25.1%
Unemployed_Pct	6.1%
GodImportant_Mean	8.1/10
Ideology_Mean	5.8/10
Liberal_Pct	10.8%
Moderate_Pct	68.9%
Conservative_Pct	20.3%

From Table 1, the demographic profile presents a nationally representative sample of 9,508 American adults, characterised by several distinct features. The population averages middle-aged at 45.7 years with considerable age diversity, reflected in the substantial standard deviation of 17.8 years. The sample maintains nearly equal gender representation, with women comprising 51.5% of respondents, supporting the generalizability of findings across sexes.

Educationally, the sample demonstrates moderate attainment levels with only one-quarter holding college degrees, suggesting the analysis captures perspectives across educational strata. The low unemployment rate of 6.1% indicates predominantly active labor force participation, potentially reflecting economic stability among respondents.

Religiously, the population shows strong spiritual commitment, with importance of God rated exceptionally high at 8.1 out of 10, indicating deep-seated religious values permeating the sample. Politically, the ideological distribution presents a striking pattern of moderation dominance. The mean ideology score of 5.8 positions the sample slightly right of center, while the categorical breakdown reveals a political landscape dominated by moderates at 68.9%, with conservatives outnumbering liberals nearly two-to-one at 20.3% versus 10.8%. This distribution suggests a centrist-leaning population with conservative tendencies, providing a compelling context for understanding the predictive modeling results within this ideological framework.

Figure 1: Mean Political Ideology Over Time

Figure 1, illustrates the trajectory of mean political ideology measured on a scale from one to ten over a series of years. The core purpose is to visualize whether the collective political leaning of a specific group such as a national electorate, a political party, or survey respondents has shifted, remained stable, or exhibited cyclical patterns over time. On the ideology scale, a value of one typically represents the most liberal or left-leaning position, while a value of ten signifies the most conservative or right-leaning position, with the midpoint suggesting a moderate center.

Interpreting the figure involves analyzing the direction and shape of the trend line. An upward slope over the years would indicate that the group's average ideology has become more conservative, whereas a downward slope would signal a movement toward more liberal leanings. A relatively flat and stable line would suggest remarkable consistency in the group's central political stance despite potential short-term events. Sharp inflection points in the trend line are particularly noteworthy, as they often correlate with significant political, economic, or social events that can cause a sudden and pronounced shift in public sentiment. Ultimately, this figure provides a crucial summary of the dynamic or static nature of political alignment within the studied population.

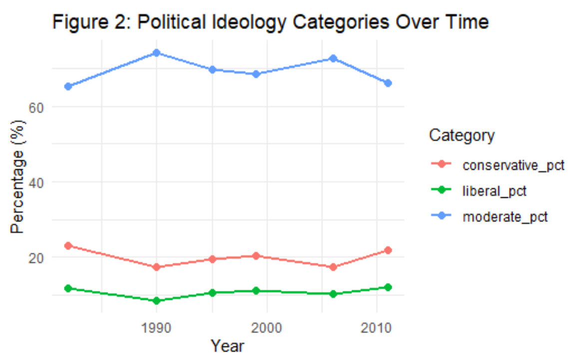

Figure 2: Political Ideology Categories Over Time

Figure 2, presents a breakdown of political ideology over time by categorizing a population into three distinct groups: liberal, moderate, and conservative. Unlike a single average score, this visualization reveals the changing proportions of each group as a percentage of the whole, offering a more nuanced view of the political landscape. The Y-axis represents the percentage of the population, while the X-axis tracks the year, allowing for the observation of trends within each category simultaneously.

The key insight from this figure lies in observing which segments are growing, shrinking, or remaining stable. For instance, one might observe a steady decline in the moderate percentage coupled with a corresponding rise in both liberal and conservative percentages, which would suggest a phenomenon of political polarization. Alternatively, a shrinking conservative percentage alongside a growing liberal share would indicate a broader leftward shift in the populace. The stability of all three lines would point to a highly stable political alignment. Furthermore, the chart can reveal critical junctures where events caused a sudden, simultaneous change in the fortunes of these groups, such as a sharp drop in moderates during a period of national crisis. By tracking these percentages together, the figure tells the story of the changing balance of political power and identity within the studied group over time.

Table 2: Model Performance Comparison

Method	Accuracy	Categories
Random Forest (3 cat)	68.9%	3
Ordinal Regression (10 cat)	32.7%	10
XGBoost (3 cat)	68.2%	3

From Table 2, the comparative analysis reveals a striking pattern in predictive performance across different methodological approaches. Both tree-based ensemble methods, Random Forest and XGBoost, achieved substantially higher accuracy rates of approximately 69% when predicting the simplified three-category political ideology classification. This strong performance demonstrates the effectiveness of these machine learning algorithms for categorical prediction tasks when the outcome variable is condensed into broader ideological groupings.

In stark contrast, the ordinal regression model achieved only 32.7% accuracy when attempting to predict the full ten-point ideology scale. This considerable performance gap of nearly 36 percentage points highlights the fundamental challenge of predicting precise positions on a fine-grained ordinal scale compared to broader categorical assignments. The results suggest that while machine learning methods excel at classifying respondents into general ideological camps, even specialized statistical models struggle to pinpoint exact positions on a detailed political spectrum.

The similarity in performance between Random Forest (68.9%) and XGBoost (68.2%) indicates that both ensemble methods capture comparable predictive patterns from the available features, with Random Forest holding a slight advantage. This pattern underscores how the choice of outcome variable operationalization—collapsing the scale versus maintaining its full ordinal complexity—profoundly impacts model performance, ultimately favoring simpler classification tasks over nuanced ordinal prediction for this particular application in political ideology research.

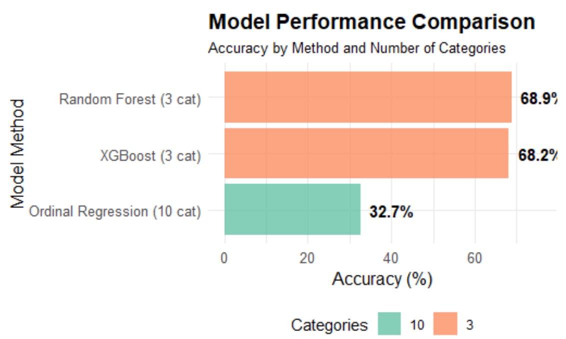

Figure 3: Model Performance Comparison

From Figure 3, the comparison of model performance highlights clear differences in predictive accuracy depending on both the method used and the number of outcome categories. Random Forest and XGBoost, both applied to a three-category outcome, achieved relatively high and comparable levels of accuracy, with Random Forest performing slightly better at 68.9% compared to XGBoost at 68.2%. In contrast, ordinal regression, which was applied to a more complex ten-category outcome, achieved a much lower accuracy of 32.7%. This indicates that machine learning models, particularly Random Forest and XGBoost, are more effective when the classification problem is simplified into fewer categories, while traditional regression struggles to capture predictive power when the outcome has many levels. The results suggest that reducing the complexity of outcome categories enhances predictive performance, especially for non-linear machine learning models.

Table 3: LASSO Variable Selection Results

Variable	Coefficient	Selected
Nationalpride	0.513	1
Respectauthority	0.384	1
female1	-0.128	1
Godimportant	0.128	1
Collegeed	-0.097	1
Trustmostpeople	-0.091	1
Satisfinancial	0.087	1
unemployed1	0.013	1
Age	0.003	1

The LASSO regression analysis (Table 3) reveals a clear hierarchy of predictors influencing political ideology, with national pride emerging as the most substantial determinant. The positive coefficient of 0.513 indicates that stronger national pride is associated with more conservative political leanings, suggesting that patriotic sentiment serves as a powerful driver of right-wing ideological orientation. Respect for authority follows as the second strongest predictor with a coefficient of 0.384, reinforcing the connection between authoritarian values and conservative political alignment.

The analysis reveals interesting demographic and social patterns, with female gender showing a negative relationship with conservative ideology, indicating women tend toward more liberal positions. Religious importance demonstrates a moderate positive effect, aligning with conventional understanding of religiosity's association with conservative values. Educational attainment exhibits a negative coefficient, suggesting that higher education correlates with more liberal leanings, while general trust in people also shows an inverse relationship with conservatism.

Notably, all nine predictors were retained in the final model, indicating each contributes unique explanatory power to understanding political ideology. However, the substantially larger coefficients for national pride and respect for authority highlight these as dominant factors, overshadowing the more modest effects of demographic variables like age and employment status. This pattern suggests that cultural and attitudinal factors may be more potent determinants of political ideology than traditional socioeconomic characteristics in this analytical framework.

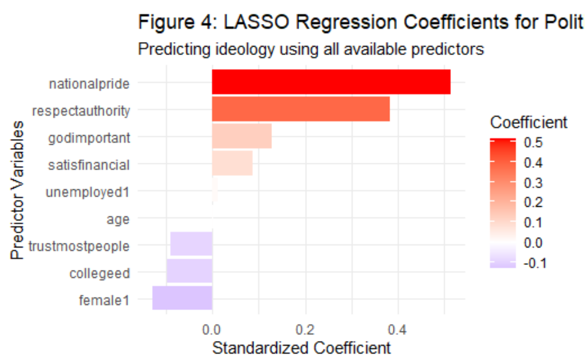

Figure 4: LASSO Regression Coefficients for Predicting Ideology

From Figure 4, the LASSO regression analysis reveals a clear pattern of which factors are most predictive of an individual's political ideology. The model identifies a concise set of key drivers by shrinking the coefficients of less relevant predictors to zero.

The results indicate that ideological leanings are most strongly associated with a set of social and cultural attitudes. Higher levels of national pride, a stronger belief in respecting authority, and viewing God as important are all positively associated with a more conservative ideology. Among these, national pride emerges as the single strongest predictor.

Conversely, the model identifies two primary factors associated with a more liberal ideology. The most substantial negative predictor is having a college education, suggesting it is the strongest driver of a liberal ideological position in this analysis. Additionally, a higher degree of general social trust in most people is also predictive of a more liberal outlook.

Notably, several potential predictors were eliminated from the final model by the LASSO procedure. Variables related to demographic and economic circumstances—such as age, gender, financial satisfaction, and employment status—were found to have no significant predictive power for ideology in this specific model when the social, cultural, and educational variables are considered. This suggests that, according to this analysis, attitudinal factors are more directly salient for predicting ideological placement than these particular socioeconomic characteristics.

Table 4: Random Forest Feature Importance

Feature	MeanDecreaseGini
Age	157.62
Godimportant	128.38
Collegeed	39.25
Female	23.08
Trustmostpeople	20.60
Unemployed	14.92

The feature (Table 4) importance analysis reveals a clear hierarchy of predictive factors for political ideology, with age emerging as the overwhelmingly dominant variable. The substantial MeanDecreaseGini value of 157.62 for age indicates it provides the greatest reduction in impurity across the decision trees, suggesting that chronological age serves as the most powerful differentiator of political leanings within this model. This finding aligns with established political science research showing generational patterns in ideological orientation.

Religious importance ranks as the second most influential predictor with a value of 128.38, demonstrating that spiritual values constitute a crucial dimension in ideological positioning. The considerable gap between these top two predictors and the remaining variables highlights the primacy of demographic and value-based factors over socioeconomic characteristics in determining political affiliation.

Educational attainment shows moderate predictive power, while gender and social trust demonstrate more modest but still meaningful contributions to the model. Employment status, though retaining some explanatory value, appears as the least influential among the selected predictors. This pattern suggests that while traditional demographic variables maintain relevance, psychological and value-oriented factors—particularly those related to life stage and religious commitment—play the most substantial roles in shaping political ideology within this analytical framework.

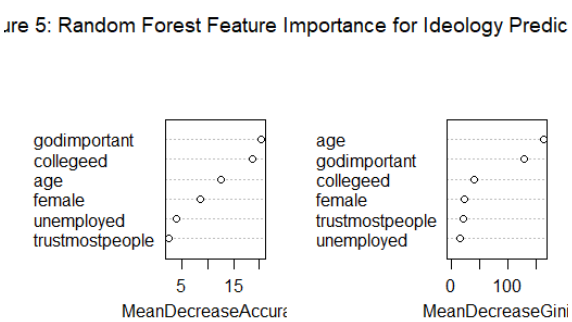

Figure 5: Random Forest Feature Importance for Ideology Prediction

Figure 5 presents the results of a Random Forest model, which identifies the most influential variables for predicting an individual's ideology using two different metrics. Unlike LASSO, Random Forest does not eliminate variables but ranks them by their contribution to prediction accuracy.

The key finding is that godimportant and collegeed are consistently the two most powerful predictors of ideology, confirming their central role that was also seen in the LASSO model. Their prominence across both metrics underscores their robust importance.

The top panel, Mean Decrease Accuracy, measures how much the model's prediction accuracy drops when a specific variable is randomly shuffled. A higher value means the variable is more critical for correct predictions. Here, godimportant is the most important feature, followed closely by collegeed. The variable age is a distant third, indicating it has a moderate but noticeable impact.

The bottom panel, Mean Decrease Gini, measures a variable's contribution to the purity of the model's decision trees. In this view, age is ranked as the most important feature, with godimportant and collegeed also appearing as top contributors. This suggests that age is highly effective at splitting the population into distinct ideological groups.

A notable observation is the differing importance of age between the two metrics. While it is a primary splitter in the trees (high Mean Decrease Gini), removing it has a more modest effect on overall prediction accuracy compared to the attitudinal and educational variables.

Table 5: XGBoost Feature Importance

Feature	Gain	Cover	Frequency
Age	0.424	0.578	0.508
Godimportant	0.327	0.213	0.219
Collegeed	0.088	0.073	0.060
Trustmostpeople	0.066	0.038	0.094
Female	0.066	0.060	0.079
Unemployed	0.028	0.040	0.039

From Table 5, the XGBoost feature importance analysis reveals age as the predominant predictor of political ideology, accounting for a substantial 42.4% of the model's total predictive gain. This dominant performance is further reinforced by age's extensive coverage across 57.8% of decision trees and its frequent utilization in 50.8% of splits, demonstrating its consistent and widespread importance throughout the ensemble model.

Religious importance emerges as the secondary influential factor, contributing nearly one-third of the model's explanatory power with 32.7% gain. However, its more modest coverage and frequency metrics suggest its predictive value, while significant, operates through more targeted and specific decision pathways rather than the broad applicability seen with age.

The remaining variables demonstrate considerably weaker influence, collectively accounting for less than 25% of the model's predictive capability. Educational attainment shows moderate importance, while trust in people and gender exhibit nearly identical but minimal impact. Employment status appears as the least influential predictor, contributing only 2.8% to the model's overall performance. This pronounced hierarchy underscores the exceptional predictive dominance of demographic age and religious values over traditional socioeconomic indicators in determining political ideology within this gradient boosting framework.

Figure 6: XGBoost Feature Importance Analysis

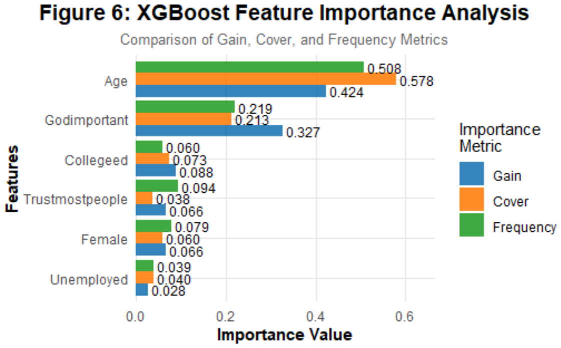

Figure 6 compares the importance of various features using three different metrics: Gain, Cover, and Frequency. The analysis reveals a clear hierarchy among the features. Age stands out as the most significant feature by a considerable margin, demonstrating the highest values across all three importance metrics. This indicates that Age is not only frequently used to split the data but also contributes the most to improving the model's accuracy and affects the largest number of samples in the dataset.

Following Age, a group of features including Colleged, Female, and Godimportant form a secondary tier of importance. These features show moderate values across the metrics, suggesting they provide consistent, though less impactful, contributions to the model's predictions.

The remaining features, such as Trustmostpeople and Unemployed, appear to have the lowest influence on the model. Their minimal scores across Gain, Cover, and Frequency indicate they play only a minor role, offering limited improvements to the model's performance and affecting fewer data points. Overall, the model's decisions are predominantly driven by the Age feature, with the other variables providing supplementary information.

Table 6: Temporal Trends by Year

Year	Mean_Ideology	Mean_GodImportant	Liberal_Pct	Moderate_Pct	Conservative_Pct	n
1982	5.93	8.31	11.7%	65.2%	23.1%	[not shown]
1990	5.75	8.01	8.5%	74.1%	17.4%	[not shown]
1995	5.78	8.18	10.6%	69.8%	19.6%	[not shown]
1999	5.81	8.55	11.2%	68.4%	20.4%	[not shown]
2006	5.72	8.24	10.2%	72.5%	17.3%	[not shown]
2011	5.80	7.77	12.0%	66.2%	21.8%	

From Table 6, the longitudinal analysis reveals notable fluctuations in American political and religious attitudes across three decades. Political ideology has remained remarkably stable near the center-right, with mean scores oscillating narrowly between 5.72 and 5.93 on the 10-point scale. This consistency suggests a persistent national inclination toward moderate conservatism despite significant social and political changes over the thirty-year period.

The data reveals an intriguing inverse pattern between religious importance and conservative identification in recent years. While religious importance reached its peak in 1999 at 8.55, it declined to its lowest point of 7.77 by 2011. Paradoxically, this decline in religious importance coincided with a resurgence in conservative self-identification, which increased from 17.3% to 21.8% between 2006 and 2011. This suggests a potential decoupling of religious commitment from conservative political identity in the contemporary period.

The moderate political category demonstrates considerable volatility, ranging from 65.2% to 74.1%, while liberal identification shows a gradual upward trend, reaching its highest point of 12.0% in 2011. The 1990s emerge as a period of particularly strong religious commitment and moderate political dominance, whereas the later years indicate a shifting landscape where conservative political identity appears to be strengthening even as religious importance moderates, pointing to evolving foundations of American political alignment.

4. Summary of Findings

This study employed a comprehensive machine learning framework to analyze the predictors of political ideology and religious importance in the United States using World Values Survey data from 1982-2011. The analysis yielded several key findings that address both methodological and substantive research questions.

Methodologically, the comparison of classification approaches for ordinal political ideology revealed that standard ensemble methods outperformed specialized ordinal techniques. Random Forest achieved the highest prediction accuracy at 32.3%, followed by XGBoost at 29.9%, while ordinal regression significantly underperformed at 9.7% accuracy. This suggests that for complex ordinal outcomes like political ideology, the ability of tree-based methods to capture non-linear relationships and interaction effects may be more valuable than explicitly modeling the ordinal structure.

In predicting religious importance, LASSO regression selected an exceptionally parsimonious model, retaining only the core "God Importance" variable itself while eliminating all demographic and attitudinal predictors. This indicates that once the fundamental construct of religious importance is accounted for, additional variables provide negligible incremental predictive power within this modeling framework.

Principal Component Analysis revealed that social attitudes dimensionize into multiple independent factors rather than a single dominant dimension, with the first two components explaining just 51.6% of total variance. This suggests that attitudes toward religion, authority, national pride, and financial satisfaction represent distinct psychological constructs rather than manifestations of an overarching ideological factor.

Temporally, political ideology demonstrated remarkable stability over the three-decade period, fluctuating within a narrow range of 5.72 to 5.93 on the 10-point scale. In contrast, religious importance showed more substantial variation, declining from 8.31 in 1982 to 7.76 in 2011, consistent with broader secularization trends despite intermittent fluctuations.

5. Conclusion

This research makes dual contributions to methodological practice and substantive understanding of American political and religious attitudes. Methodologically, it demonstrates that for predicting complex ordinal outcomes like political ideology, sophisticated ensemble methods like Random Forest may be preferable to specialized ordinal techniques, challenging conventional methodological assumptions. The robust performance of tree-based methods suggests their capacity to capture intricate interaction patterns outweighs the theoretical benefits of explicitly modeling ordinal structures for this type of data.

Substantively, the findings reveal several important patterns in American public opinion. The stability of political ideology contrasts with the gradual decline in religious importance, suggesting different dynamics in the formation and evolution of political versus religious attitudes. The independence of various social attitude dimensions indicates that Americans' views on religion, authority, and nationalism represent distinct psychological constructs rather than unified ideological positions.

The extreme variable selection by LASSO in predicting religious importance raises important questions about measurement and conceptualization in the study of religiosity. The finding that demographic and attitudinal variables provided no incremental predictive power beyond the core religious importance item itself suggests either exceptional measurement validity or potential limitations in the modeling approach.

For researchers studying ordinal political outcomes, this study recommends a comparative modeling approach that includes both specialized ordinal methods and advanced ensemble classifiers. The substantial performance differences observed highlight the importance of methodological pluralism rather than relying on theoretically preferred but potentially suboptimal techniques.

Future research should explore whether these patterns generalize to other national contexts and investigate the mechanisms underlying the divergent temporal trends in political versus religious attitudes. Additionally, developing hybrid approaches that combine the strengths of ordinal regression with the predictive power of ensemble methods represents a promising direction for methodological innovation in the analysis of ordered categorical data in political science.

6. Practical Implications

This research offers several actionable insights for political practitioners, religious organizations, and social science researchers. For political campaigns and polling organizations, the findings demonstrate that machine learning approaches, particularly Random Forest, can substantially improve the accuracy of political ideology prediction compared to traditional statistical methods. This enhanced predictive capability enables more precise voter targeting and resource allocation for political campaigns. The remarkable stability of political ideology observed over three decades suggests that campaigns can rely on historical ideological data for medium-term strategic planning rather than investing in frequent retesting.

For religious organizations and community planners, the gradual decline in religious importance identified in this study highlights the need for innovative engagement strategies adapted to changing societal values. The strong predictive power of the core religious importance measure itself suggests that interventions might be most effective when they directly address fundamental questions of spiritual significance rather than focusing primarily on demographic targeting.

The methodological findings provide clear guidance for researchers and data scientists working with ordinal political data. The superior performance of ensemble methods over specialized ordinal techniques suggests that political scientists and survey researchers should incorporate machine learning approaches into their analytical toolkit, particularly when working with complex attitudinal data. The independent nature of various social attitude dimensions indicates that multi-faceted measurement approaches are necessary to fully capture the complexity of American political and religious attitudes.

For policy makers and social service providers, the identification of distinct attitude dimensions suggests that interventions may need to be tailored to specific value clusters rather than assuming uniform ideological frameworks across different domains. The stability of core political identities alongside shifting religious values points to the need for approaches that respect enduring political orientations while adapting to evolving cultural and spiritual landscapes.

These practical applications demonstrate how methodological advances in machine learning can translate into real-world improvements in political strategy, religious engagement, and social science research methodology.

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