Religious Affiliation Prediction

DSAN 6600 April 2025

Georgetown University

TEAM

Lizzie Healy Sophia Rutman Courtney Green Caroline Delva









Religious Affiliation Prediction

Survey Data Supervised Learning Religion multi-class classification Hypotheses



Data

Pew Research Center Religious Landscape Study



Surveyed in 2023-2024



Address Based Sampling (ABS)

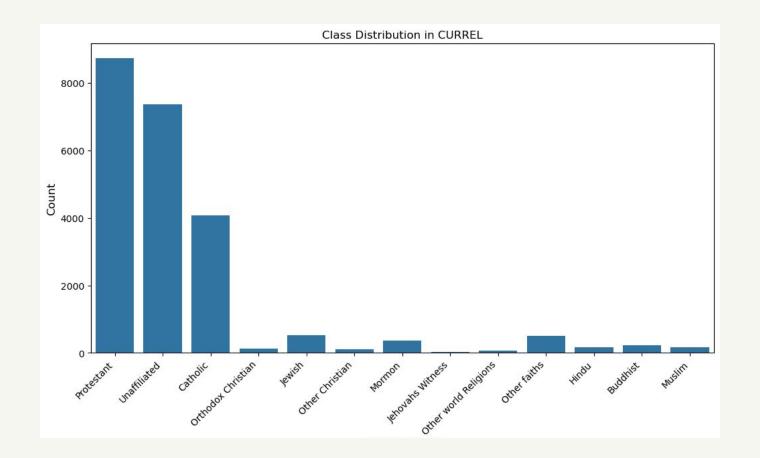


36,908 people responded

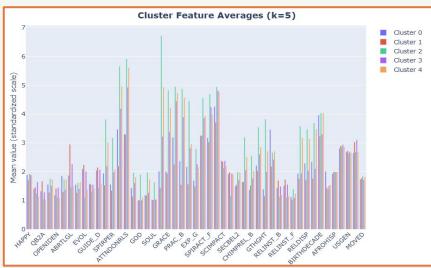


130 questions asked

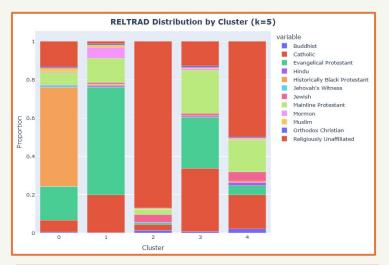
Current Religion (Currel): Protestant | Unaffiliated | Catholic | Jewish | Mormon | Buddhist | Muslim | Hindu | Orthodox Christian | Jehovah's Witness | Other Christian | Other world religions | Other faiths

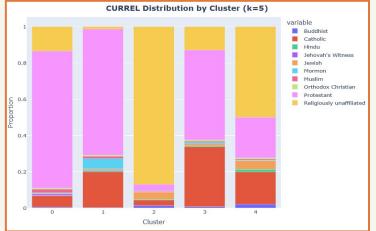


Clustering EDA

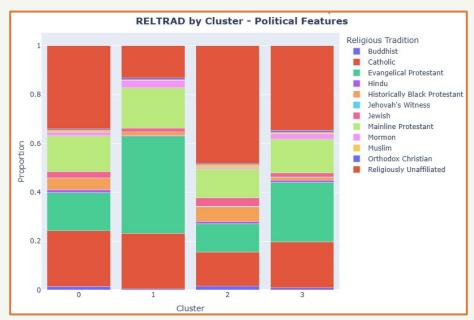


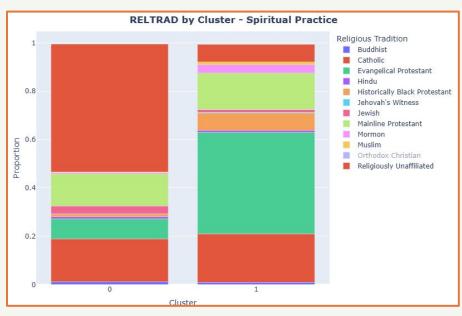
- Clusters reflect distinct socio cultural profiles not just religion but values, practice, and belief.
- **RELTRAD shows richer variation** within Protestant subgroups; **CURREL oversimplifies** into Protestant vs. unaffiliated.
- Religious identity \neq worldview high religiosity spans multiple clusters, and some unaffiliated groups show strong spiritual engagement.





Category-Specific Clustering





Clustering reveals behavioral patterns that religious labels miss. Identity and practice often diverge — especially in spiritual domains — creating intra-group variation (noise) that complicates classification. This could help explain why we weren't able to achieve a perfect model accuracy—there's no clean mapping between belief, behavior, and affiliation.

Feature Selection

Normalization: StandardScaler applied to input features

Label Encoding: Religious groups mapped to integers for model training.

Stepwise Feature Selection: Random Forest Classifier

- Selected 50 features via 3-fold stratified CV
- Accuracy after selection: **65.4**%

Multi-Layer Perceptron

Grid Search

Optimizers: rmsprop, sgd, adam Activations: relu, tanh, leaky_relu Regularization: None, L1, L2

Regularization Strengths: 0.001, 0.01, 0.1

Dropout: 0, 0.2, 0.5

Best Configuration (Validation):

SGD Optimizer + Tanh Act. Function, L1(0.001), No Dropout

- Validation Accuracy: **67.7**%
- Precision: 65.2%
- Recall: 46.1%
- F1: 48.8%

Hyperparameters Tuning

Input Layer: 50 features (after scaling and selection) Hidden Layers:

• 2 Dense hidden layers (64 units each)

Activation functions and regularization tuned via grid search

Output Layer: 12 neurons with Softmax activation Loss Function: Sparse categorical cross-entropy

Training Settings:

- Early Stopping: Patience = 10 epochs
- Batch Size: 16
- Max Epochs: 80 (early stop if no improvement)

Test Set Performance

- Accuracy: 68%
- Macro Fl Score: 0.44
- Weighted F1 Score: 0.66

Conclusion:

- Strong prediction of dominant classes (Protestant, Religiously unaffiliated).
- Poor recall for rare classes (Orthodox Christian, Jehovah's Witness, Buddhist).
- Class imbalance likely affecting minority class predictions.

Performance

Model

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Quadratic Discriminant Analysis

Model 1) Full Currel

Model 2) Christian Non-Christian Unaffiliated

Model 3) Protestant
Unaffiliated
Catholic
Jewish
Mormon
Other
Jehovah's Witness

All Predictor
Variables

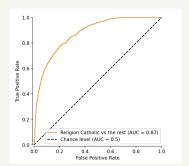
SMOTE

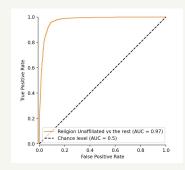
Hyperparameter Tuning (reg_param)

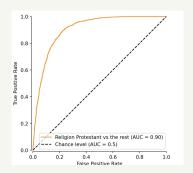
Selected Variables (SF)

QuadraticDiscriminantAnal ysis (sklearn)

QDA	Baseline Model		With Selected Features					
	Accuracy	Weighted F-1	Accuracy	Weighted F-1				
Model 1	0.67	0.70	0.60	0.66				
Model 2	0.89	0.90	0.91	0.91				
Model 3	0.68	0.71	0.65	0.69				







Model 1

10 classes

Test Accuracy: 75.47%

Transformer

Model 2

13 classes

Test Accuracy: 94.77%

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No decoder

Embeddings

Hyperparameter Tuning Decoders predict the next token in a sequence - not applicable to multi-class classification

Embeddings created by the encoder are the main reason why the transformer outperforms MLP

- Embedding Dimension
- Feedforward Dimension
- Number of Attention Heads
- Number of encoding layers
- Dropout regularization
- Learning Rate

10 Classes:

13 Classes:

					Со	nfusio	n Mat	rix				
	0 -	762	47	2	0	1	3	0	1	2	97	- 700
	٦ -	146	200	0	0	0	4	0	1	0	51	
	٦ -	14	1	9	0	0	0	0	0	0	3	- 600
	m -	13	0	0	0	0	1	0	0	0	4	- 500
abel	4 -	1	0	0	0	2	0	0	0	0	1	- 400
True Label	ი -	7	7	0	0	0	11	0	0	0	15	
	9 -	2	3	0	0	0	0	3	1	2	3	- 300
	۲-	2	2	0	0	0	2	0	3	1	13	- 200
	ω -	2	1	0	0	0	0	1	0	10	2	- 100
	ი -	52	19	0	0	0	2	1	0	1	643	
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								Con	fusio	n Ma	atrix						
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	1	-	0	409	0	0	0	0	0	0	0	0	0	0	0	0	800
	2	-	0	0	41	0	0	0	0	0	0	0	0	0	0	0	- 700
	m	-	0	0	0	4	0	4	0	0	0	0	0	0	0	0	
	4	_	0	0	0	0	0	2	1	0	0	0	0	0	0	0	- 600
	2	-	0	0	0	0	0	5	0	0	0	0	0	0	0	0	- 500
abel	9	-	0	0	0	0	0	1	53	0	0	0	0	0	0	0	300
True Label	7	-	0	0	0	0	0	0	13	6	0	0	0	0	0	0	- 400
_	œ	-	0	0	0	0	0	0	3	16	3	0	0	0	3	0	
	6	-	0	0	0	0	0	0	0	0	0	0	0	0	22	0	- 300
	10	-	0	0	0	0	0	0	0	0	0	0	0	0	3	0	- 200
	11	-	0	0	0	0	0	0	0	0	0	0	0	0	58	0	
	12	-	0	0	0	0	0	0	0	0	0	0	0	0	740	1	- 100
	13	-	0	0	0	0	0	0	0	0	0	0	0	0	0	9	
			ó	1	2	3	4	5 Pre	6 edicte	7 ed Lal	8 pel	9	10	11	12	13	- 0

Conclusion

Best Model:

- Transformer Model 2 (13 classes)
- Test Accuracy: 94.77%

Why it performed best:

- Captured nuanced patterns via embeddings and attention
- Outperformed MLP and QDA across all metrics

Model Limitations:

- Poor recall for minority classes (e.g., Jehovah's Witnesses)
- Religious identity ≠ behavior → intra-group noise
- Class imbalance affected performance across all models

Future Work:

- Implement class rebalancing (oversampling, weights)
- Explore multi-label or probabilistic affiliation models
- Integrate open-text responses for richer context
- Use interpretability tools (e.g., SHAP, attention maps)

Thank You