Week 9 Report

The following represents the training and validation accuracy for the models generated in the last three reports:

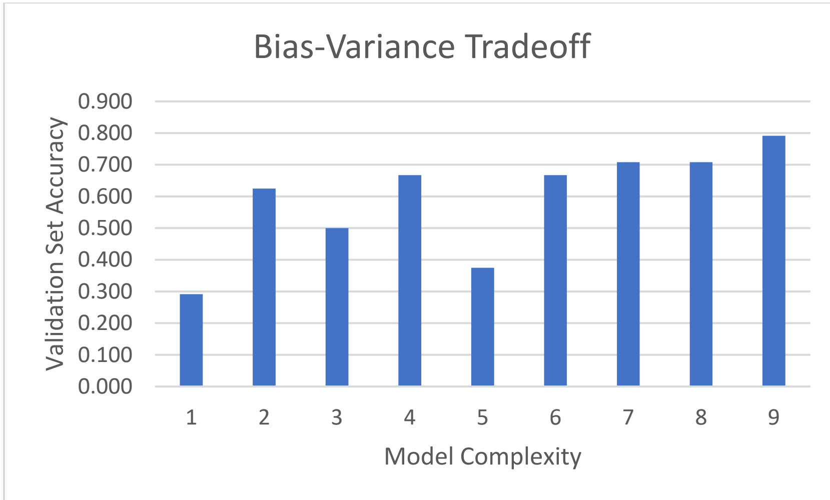
Simple OLS	Training	Validation	Number of Features
Subset Selection	0.675	0.292	15
All variables	0.927	0.500	191
Reverse Variable Selection	0.864	0.625	27

XGBoost	Training	Validation	Number of Features
All variables	1.000	0.667	191
Reverse Variable Selection	1.000	0.667	93
Variable Selection	1.000	0.375	18

Random Forest	Training	Validation	Number of Features
All variables	0.953	0.708	84
5-Fold Hyperparameter Selection	0.880	0.708	69
Optimized Parameter Selection	0.895	0.792	44

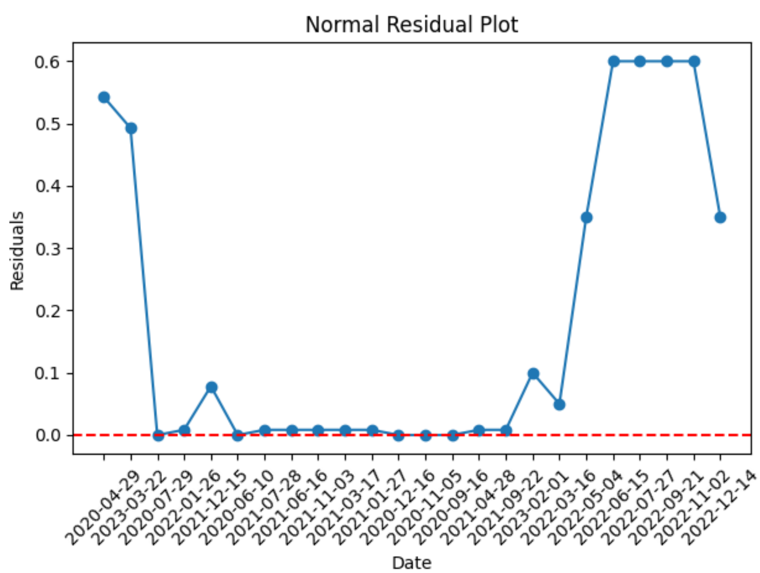
Incorporating the training accuracy and the number of features serves the purpose of distinguishing models that may achieve apparent success solely through overfitting. Notably, the adjusted R^2 exceeding 1 in most of the previous models stemmed from an imbalance between the number of features and the number of observations predicted. Consequently, selecting the most accurate model may not necessarily be the optimal approach when determining the preferred model for future applications. Other considerations, such as generalization capabilities and the potential for overfitting, are crucial factors to be taken into account in this decision-making process.

The optimized parameter selection version of the Random Forest model exhibits remarkable accuracy in both the training and validation sets, outperforming some of the other models that utilize a larger number of features but do not achieve comparable results. In contrast, the XGBoost models clearly suffer from overfitting, evident from their excessively high training accuracy and subpar validation accuracy. The OLS models perform commendably, yet they fall short of matching the accuracy achieved by the Random Forest models. Notably, the "All Variables" Random Forest model boasts higher training accuracy compared to the optimized parameter selection model; however, its validation accuracy is weaker, suggesting potential overfitting, likely attributed to the excessive number of features employed.



1	Subset Selection	**Simple OLS**
2	Reverse Variable Selection	
3	All variables	
4	All variables	**XGBoost**
5	Variable Selection	
6	Reverse Variable Selection	
7	All variables	**Random Forest**
8	5-Fold Hyperparameter Selection	
9	Optimized Parameter Selection	

Running the model against the test dataset, it achieves an accuracy of 0.667. This is not as strong as the validation test, which may suggest some level of bias. That said, a look at the residual plot merits some discussion.



No only does the model never overestimate, but the consistent error in the latter half suggests some autocorrelation in errors—or that the activity in the late 2022 was exigent and literally unpredictable.

It is concerning that these are also some of the only times where there is monetary policy action at all, and the model was unable to capture the true magnitude.

Metric	Training Set	Validation Set	Test Set
MSE	0.00621728	0.0286458	0.0677083
RMSE	0.0788497	0.169251	0.260208
R^2	0.845522	0.559265	0.186441
Adjusted R^2	0.694262	1.14277	1.26355
Accuracy	0.900524	0.666667	0.666667

The accuracy measures demonstrate a diverse array of interpretations. Firstly, the substantial disparity in R^2 values across the models indicates a notable weakness in the model's ability to generalize, possibly resulting from overfitting. The observation that the adjusted R^2 also remains higher than the number of observations further reinforces the indication of potential overfitting. Addressing this issue necessitates either imposing more stringent restrictions on the number of features during data augmentation or seeking an alternative repository housing all the FOMC minutes as downloadable text. This avenue holds promise for further exploration. Notably, the accuracy remains consistent between the validation and test sets, implying a certain level of consistency in generalization; however, the model's performance falls short of real-world application standards.

Earlier iterations of this analysis included a stepwise approach to analyzing monetary policy action. Namely, the first step would be to implement a logistic model to predict the direction of monetary policy (“Increase”, “Decrease”, or “Hold”). Then, a regression model would predict the degree to which monetary policy would “Increase” or “Decrease”. This approach may still have some merit.