Predicting Recession From Economic Indicators

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Objective

Using quarterly economic indicators from Federal Reserve database, predict if a given quarter is under recession. Identify the key economic indicators that are highly predictive of recession.

Data Description

The Federal Reserve Economic Data is a publicly available dataset [1]. The data source has downloadable economic indicators aggregated daily or monthly or quarterly. During data preparation, these features are aggregated at quarterly level and 241 quarters that has most non-missing feature values from Q1 1961 to Q1 2021 is used in the analysis. Some variables with a lot of missing values are later dropped. Additional features are derived from original data to better represent the market reality in predicting recession.

Target variable and Features are:

- Target variable: Quarterly Recession Indicator (USRECQ). Recession:1 No-Recession: 0.
- Change in real private inventories (CBIC1). Represents inventory volume change from a year ago quarter.
- Permits issued for new privately-owned housing units in the quarter (PERMIT_SUM)
- Derived: Maximum monthly change in housing permits within the quarter (PERMIT_DIFF)
- Volume of retail trade sales in the quarter (SLR). Data missing from Q3 2018.
- Derived: Year over Year percentage change in retail trade sales (YoYC_PER_SLR)
- Average quarterly change in treasury bill yield between 10 and 2 years (T10_Mean).
- Average unemployment rate in each quarter (UNRATE_MEAN)
- Derived: Maximum monthly change in unemployment rate within the quarter (UNRATE_DIFF).
- Housing price index in each quarter (HPI)
- Derived: Year over Year percentage change in housing price index (YoYC_PER_HPI)
- Derived Lagged Features (lg1_*): All the above features were also lagged by one quarter. These are used to predict recession in each quarter using economic indicators from previous quarter.

	USRECQ	CBIC1	PERMIT_SUM	SLR	YoYC_PER_SLR	T10_MEAN	UNRATE_MEAN	HPI	YoYC_PER_HPI
count	241	241	241	230	230	19	241	185	181
mean	0.14	35.0	4098	68.3	2.03	0.59	6.01	235.4	4.7
std	0.34	57.4	1143	20.5	3.7	0.37	1.68	114.5	4.27
median	0	35.7	4051	64.6	2.61	0.51	5.7	208.0	5.08

Table 1. Descriptive statistics of various features. 241 quarters range from Q1 1961 to Q1 2021. Treasury yield (T10_MEAN) has only 19 quarters of data. Retail sales (SLR) and Housing Price Index (HPI) have data for 230 and 185 quarters respectively. Only 14% of quarters are in recession.

Feature Exploration

Python packages such as *numpy* and *pandas* are used for computations. Packages *matplotlib* and *seaborn* are used for data visualization. Table 1 has descriptive statistics. There are 241 quarters from Q1 2016 to Q1 2021. The change in treasury bill yield (T10_MEAN) has only 19 quarters worth of data starting from Q3 2016. Retail sales is missing last 11 quarters. Housing price Index has 56 missing quarters.

Feature ranges do vary in magnitude (ex: avg of 0.59 T10_MEAN to 4098 PERMIT_SUM). USRECQ, CBIC1, YoYC_PER_SLR and YoYC_PER_HPI have high variations with standard deviations higher than their means. About 14% of quarters have recession and 86% are no-recession quarters. Data is unbalanced and has more no-recession quarters.

Figure 1 shows that the YoY change in retail sales (YoY_PER_SLR) has distribution skewed slightly to the left during quarters of no-recession. During recession quarters, the data is fairly normally distributed. The Box plot shows that recession quarters have a higher decrease in year over year change in retail sales and its values has a good separation between no-recession and recession quarters. Similar visual inspection suggests following features are likely to be important predictors of recession: year over year change in retail sales (YoY_PER_SLR), change in inventories (CBIC1), unemployment rate (UNRATE_MEAN), year over year change in housing price index (YoYC_PER_HPI) and housing permits (PERMIT_SUM).

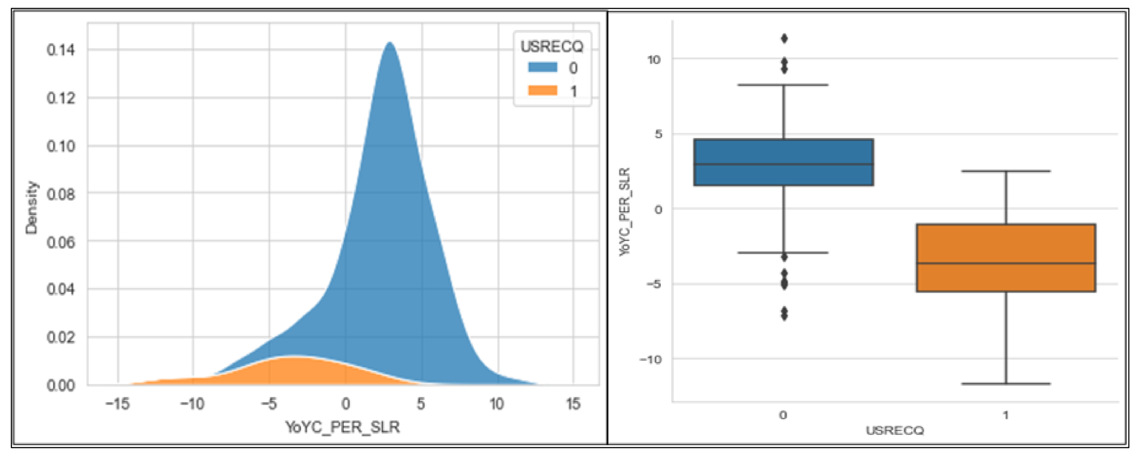

Fig. 1 Left chart shows year over year percent change in quarterly retail sales (YoY_PER_SLR) density distributions of no-recession (blue, USRECQ = 0) and recession quarters (orange, USRECQ = 1). Right chart shows same distribution in a box plot. There is a reasonably strong differentiation in values of YoY_PER_SLR between no-recession and recession quarters.

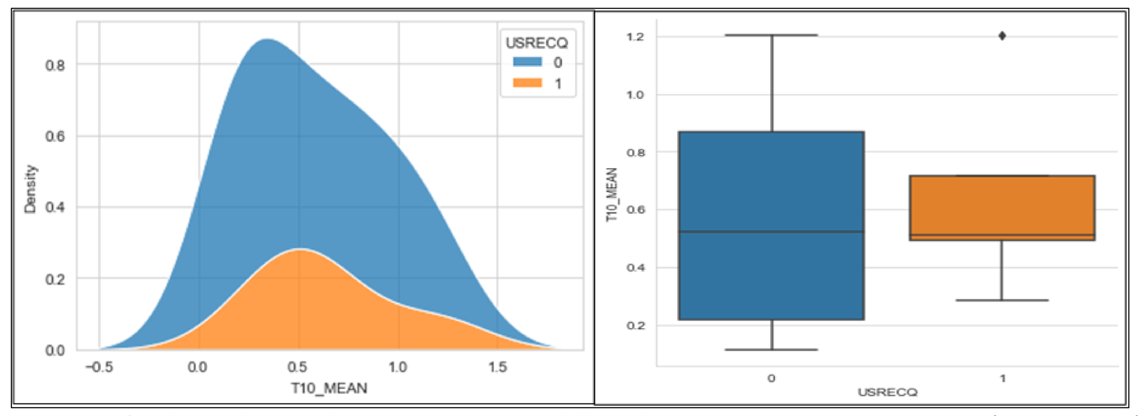

Fig. 2 Left chart shows change in treasury bill yield between 10 and 2 years (T10_MEAN) density distributions of no-recession (blue, USRECQ = 0) and recession quarters (orange, USRECQ = 1). Right chart shows same distribution in a box plot.

Figure 2 shows that the change in treasury bill yield between 10 and 2 years (T10_MEAN) has distribution skewed to the right.. The Box plot shows a big overlap between recession and no-recession, so this variable is not a good predicter. Since it also has lot of missing values, this feature is dropped from further analysis.

Recession is negatively correlated to YoY change in retail sales (-0.58) and change in inventory (-0.48). Other variables that are highly directly correlated among each other are housing permits issued and year over year change in housing price index (0.76).

Models and Results

Modeling data has 169 observations and 15 predictors with no missing data. Predictors include lagged and derived features. Data is split into 80% for training [n=135] and 20% for testing [n=34]. Training and Test data have 9.6% and 14.6% of recession quarters.

Models are built on training data and their performances are evaluated using test data. We emphasis on least error in classifying the recession quarters. Training data is balanced (i.e., recession quarters are repeated) to have equal representation of no-recession and recession quarters. Data balancing helps to improve model accuracy.

Decision trees are supervised learning methods. The algorithm first goes through the features and chooses a feature and boundary point that has maximum information to classify the target variable. Using this boundary, it subsets the data into true and false nodes. Process is repeated for each of the child nodes until leaf nodes with maximum classification accuracy could be obtained. Tree depth is adjusted to minimize overfitting. Python packages sci-kit learn *(sklearn)* and *graphviz* were used in building decision trees. Figure 3 shows a tree of depth 4 and balanced data with USRECQ as target variable. Most important economic indicators to identify recession are Lagged YoY % change in retail sales (lg1_YoYC_PER_SLR), Change in unemployment rate within the quarter [UNRATE_DIFF], Lagged change in housing permits [lg1_PERMIT_DIFF] and Lagged YoY % change in housing price index [lg1_YoYC_PER_HPI].

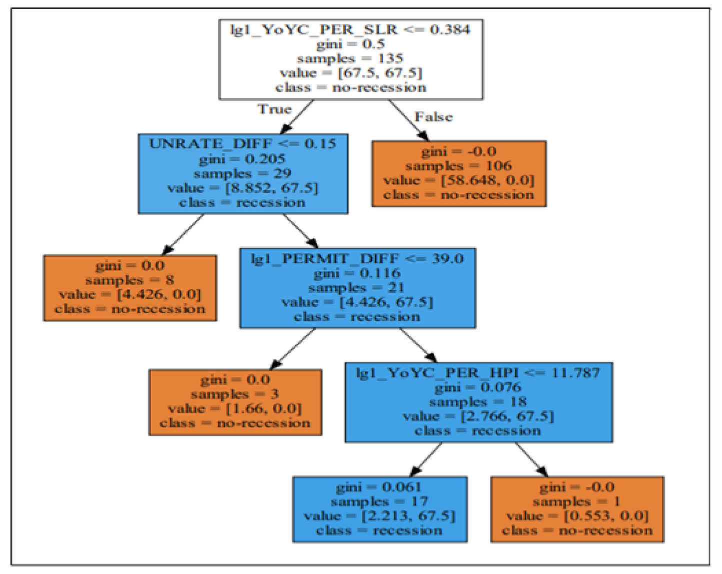

Fig. 3. Decision tree with balanced data, a max depth of four and using USRECQ as target. Orange nodes denote no-recession, and the blue nodes denote recession. Most important features to identify recession quarters are Lagged YoY % change in retail sales (lg1_YoYC_PER_SLR), Change in unemployment rate within the quarter [UNRATE_DIFF], Lagged change in housing permits [lg1_PERMIT_DIFF] and Lagged YoY % change in housing price index [lg1_YoYC_PER_HPI].

It is advantageous to predict recession in next quarter using economic indicators of current quarter. Such a decision tree model is built by using only the lagged feature values as predictor of current quarter recession. Predictive performance of this model is slightly below that of the previous model with all features.

Logistic regression classifies the binary outcomes (recession vs no-recession) using regression methods that seek to fit a linear equation that minimizes the error in classification. A logit transformation is done to the output variable so that the output is the probability of getting a value of 1 (i.e., recession quarter). We observed that the logistic regression was inferior in predicting recession.

Confusion Matrix. (Cells have count of records)		Predicted: Negative [=0] (benign)	Predicted: Positive [=1] (malignant)	
				Accuracy = [TP + TN] / [TP + TN + FP + FN]
				Precision = [TP] / [TP + FP]
Actual	Negative [=0] (benign)	True Negative [TN]	False Positive [FP]	Recall = [TP] / [TP + FN]
Actual	Positive [=1] (malignant)	False Negative [FN]	True Positive [TP]	F1 = [2*Precision*Recall] / [Precision + Recall]

Fig. 4: A confusion matrix is used to assess the model performance. It compares actual vs predicted classification record counts in test dataset. Various metrics such as accuracy, precision, recall and F1 are used to assess the model performance. Metric values range between 0 (low performance) to 1 (perfect prediction). Here we focus more on Recall as the cost of predicting a quarter has no recession when it actually is in recession is high.

Best Model and Results

A confusion matrix (Fig. 4) produces various classification accuracies. **Accuracy** defines overall predictive accuracy as % of samples that were classified correctly as either recession or no-recession quarter. **Recall** represents % of actual recession quarters that were correctly predicted. **Precision** represents % of predicted recession quarters that actually has recession. **F1 score** is a weighted average of Recall and Precision. **Best models are chosen by analyzing the highest recall in predicting recession quarters using test dataset.**

Table 3 shows performance metrics for various model configurations. Logistic regression model has a poor performance with just 50% recall and precision. **Decision Trees [Fig. 3] using balanced data with a depth of 4 has the highest recall at 100% and a precision of 83%. This is the best predictive model and is easy to interpret.** We use this decision tree model to explain the results and are discussed in conclusion section.

Model Description		Recall	F1	Precision	Accuracy
Decision Trees	Unbalanced data. Unrestricted tree depth (=5)	0.4	0.6	1	0.91
	Balanced data. Unrestricted tree depth (=8)	0.8	0.8	0.8	0.94
	Balanced data with depth 4	**1**	0.91	0.83	0.97
	Balanced data with depth 4 - Lagged Predictors only	0.88	0.82	0.77	0.93
Logistic Regression	Balanced data & Non significant features removed	0.5	0.5	0.5	0.88

Table 3: Classification metrics from confusion matrix for various model configurations. Decision Trees using balanced data with a depth of 4 has the highest recall at 100% and a precision of 83%. This is the best predictive model and is easy to interpret. Logistic regression model has a poor performance with just 50% recall and precision.

Conclusions

The Federal Reserve Economic Data [1] is used to predict if a given quarter is in recession or not. The data is processed to obtain quarter level aggregated features. Relevant features like percent changes and maximum within quarter changes were further derived. One quarter lagged features are also computed as additional features. Data is considered from Q1-1961 to Q1-2021. However, after removing missing values, there are 161 quarters to model. This data is split into 80% for training and 20% for testing. Classification models such as decision trees and logistic regression are applied to training data with recession indicator as target variable. Decision Trees using balanced data with a depth of 4 has the highest recall at 100% and a precision of 83%. This is the best model to predict recession. Based on this easily interpretable decision tree model following is observed:

A given quarter is predicted to be in Recession when:

- Last quarter year-over-year retail sales change is less than 38% (includes retail sales decreases as well) AND
- This quarter's monthly unemployment rate changes by more than 15% AND
- Last quarter drop in housing permits between high month and low month is greater than 39K AND
- Last quarter's year-over-year housing price index change is less than 11%.

References

[1] Data Source: Federal Reserve Economic Data [FRED] from St. Louis Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/

Acknowledgement

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