Crisis Detection and Early Warning System

2024-11-12

Introduction

This report analyzes temporal patterns in the interbank network to identify key banks and early warning signals of financial crises. Using centrality measures, community detection, and dynamic network analysis, the goal is to highlight systemic risks and provide insights into potential crisis indicators.

Load neccessay libraries

```r
library(readr)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(igraph)
```

```
##
## Attaching package: 'igraph'

## The following objects are masked from 'package:dplyr':
##
##     as_data_frame, groups, union

## The following objects are masked from 'package:lubridate':
##
##     %--%, union

## The following objects are masked from 'package:stats':
##
##     decompose, spectrum

## The following object is masked from 'package:base':
##
```

```
##     union
```

```
library(ggplot2)
```

Load and Prepocess the Data

```
data_files <- c('eMID_2006_2.txt', 'eMID_2007_2.txt', 'eMID_2008_2.txt', 'eMID_2009_2.txt', 'eMID_2010_
data_list <- list()

for (file in data_files) {
  df <- read.csv(file)
  if (grepl('2006', file)) {
    df$DateTime <- dmy_hms(paste(df$Date, df$Time))
  } else {
    df$DateTime <- ymd_hms(paste(df$Date, df$Time))
  }
  data_list[[length(data_list) + 1]] <- df
}

# Concatenate all the processed dataframes
data <- bind_rows(data_list)

# Sort by date
data <- data %>% arrange(DateTime)
```

Define monthly time windows based on the range of dates in the dataset

```
start_time <- min(data$DateTime)
end_time <- max(data$DateTime)
time_windows <- seq(from = start_time, to = end_time, by = "month")
```

Create snapshots of each time window

We analyze the network in monthly time windows. For each time window:

1. A snapshot of the network is created using **igraph**, with transaction amounts as edge weights.
2. Centrality measures (Degree, Betweenness, Closeness, and Eigenvector) and community membership are calculated.
3. A composite centrality score is created, and banks are categorized into "Highly Central" or "Less Central" based on the top 10% threshold
    - The composite score combines degree, betweenness, closeness, and eigenvector centralities (weighted equally) to provide an overall measure of a bank's influence.

```
temporal_metrics <- list()


for (i in 1:(length(time_windows) - 1)) {
  # Define start and end of the current time window
  window_start <- time_windows[i]
  window_end <- time_windows[i + 1]

  # Filter data for the current time window
  window_data <- data %>%
    filter(DateTime >= window_start & DateTime < window_end)

  # Create an igraph object for the current snapshot with Amount as weight
  ig_graph <- graph_from_data_frame(window_data[, c("Sender", "Receiver", "Amount")], directed = TRUE)
  E(ig_graph)$weight <- window_data$Amount  # Set weight attribute

  # Calculate weighted centrality measures
  degree <- strength(ig_graph, mode = "all", weights = E(ig_graph)$weight)  # Strength (weighted degree
  betweenness <- betweenness(ig_graph, directed = TRUE, weights = E(ig_graph)$weight)
  closeness <- closeness(ig_graph, mode = "all", weights = E(ig_graph)$weight)
  eigenvector <- eigen_centrality(ig_graph, weights = E(ig_graph)$weight)$vector

  # Apply Infomap community detection on the directed graph
  clusters <- cluster_infomap(ig_graph, e.weights = E(ig_graph)$weight)
  community_membership <- membership(clusters)

  # Create a composite centrality score
  composite_score <- 0.25 * degree + 0.25 * betweenness + 0.25 * closeness + 0.25 * eigenvector

  # Define threshold for categorization (e.g., top 10% as Highly Central)
  high_threshold <- quantile(composite_score, 0.9, na.rm = TRUE)
  categories <- ifelse(composite_score >= high_threshold, "Highly Central", "Less Central")

  # Store results for the current snapshot
  temporal_metrics[[i]] <- data.frame(
    Node = V(ig_graph)$name,
    Time = window_end,
    Degree = degree,
    Betweenness = betweenness,
    Closeness = closeness,
    Eigenvector = eigenvector,
    CompositeScore = composite_score,
    Category = categories,
    Community = community_membership
  )
}
```

Combine and Analyze Results Across Time Windows

```
# Combine all time-windowed data frames in temporal_metrics into a single data frame
temporal_metrics_df <- do.call(rbind, temporal_metrics)

#View the combined data
head(temporal_metrics_df)
```

```
##          Node                Time   Degree Betweenness    Closeness
## IT0259 IT0259 2006-02-02 09:06:21  9768.95     55.0000 0.0003650514
## IT0224 IT0224 2006-02-02 09:06:21  7673.85      0.0000 0.0003178751
## IT0171 IT0171 2006-02-02 09:06:21 16579.50      7.0000 0.0003209562
## IT0265 IT0265 2006-02-02 09:06:21  8292.60    221.2222 0.0003464643
## IT0245 IT0245 2006-02-02 09:06:21   988.10    542.9356 0.0003465760
## IT0204 IT0204 2006-02-02 09:06:21 13820.80      0.0000 0.0003080620
##         Eigenvector CompositeScore     Category Community
## IT0259 0.0043940846       2455.989 Less Central         1
## IT0224 0.0048221585       1918.464 Less Central         2
## IT0171 0.0056605362       4146.626 Less Central         3
## IT0265 0.0040306907       2128.457 Less Central         4
## IT0245 0.0000679218        382.759 Less Central         5
## IT0204 0.0098652189       3455.203 Less Central         6
```

Aggregate and Summarize Temporal Data

```r
summary_df <- temporal_metrics_df %>%
  group_by(Node) %>%
  summarize(
    AvgDegree = mean(Degree, na.rm = TRUE),
    AvgBetweenness = mean(Betweenness, na.rm = TRUE),
    AvgCloseness = mean(Closeness, na.rm = TRUE),
    AvgEigenvector = mean(Eigenvector, na.rm = TRUE),
    TimesHighlyCentral = sum(Category == "Highly Central"),
    UniqueCommunities = n_distinct(Community)
  )
```

Identify Key Banks

```r
# Identify banks that are often "Highly Central" and have many community changes
key_banks <- summary_df %>%
  filter(TimesHighlyCentral > 0 | UniqueCommunities > 1) %>%
  arrange(desc(TimesHighlyCentral), desc(UniqueCommunities))

# View key banks
print(key_banks)
```

```
## # A tibble: 203 x 7
##    Node  AvgDegree AvgBetweenness AvgCloseness AvgEigenvector TimesHighlyCentral
##    <chr>     <dbl>          <dbl>        <dbl>          <dbl>              <int>
##  1 IT02~    18753.        1118.      0.000216           0.308                 39
##  2 IT02~    12541.        1014.      0.000219           0.198                 37
##  3 IT02~    11315.         704.      0.000221           0.208                 34
##  4 IT02~     9904.         775.      0.000220           0.132                 33
##  5 IT02~     9578.         669.      0.000226           0.104                 32
##  6 BE00~    17182.         259.      0.0000974          0.221                 31
##  7 IT02~    13845.         197.      0.000204           0.191                 31
##  8 IT01~    11070.         730.      0.000221           0.170                 30
##  9 IT02~     9435.         583.      0.000222           0.157                 29
## 10 DE00~    11125.           2.28    0.000101           0.359                 28
## # i 193 more rows
## # i 1 more variable: UniqueCommunities <int>
```

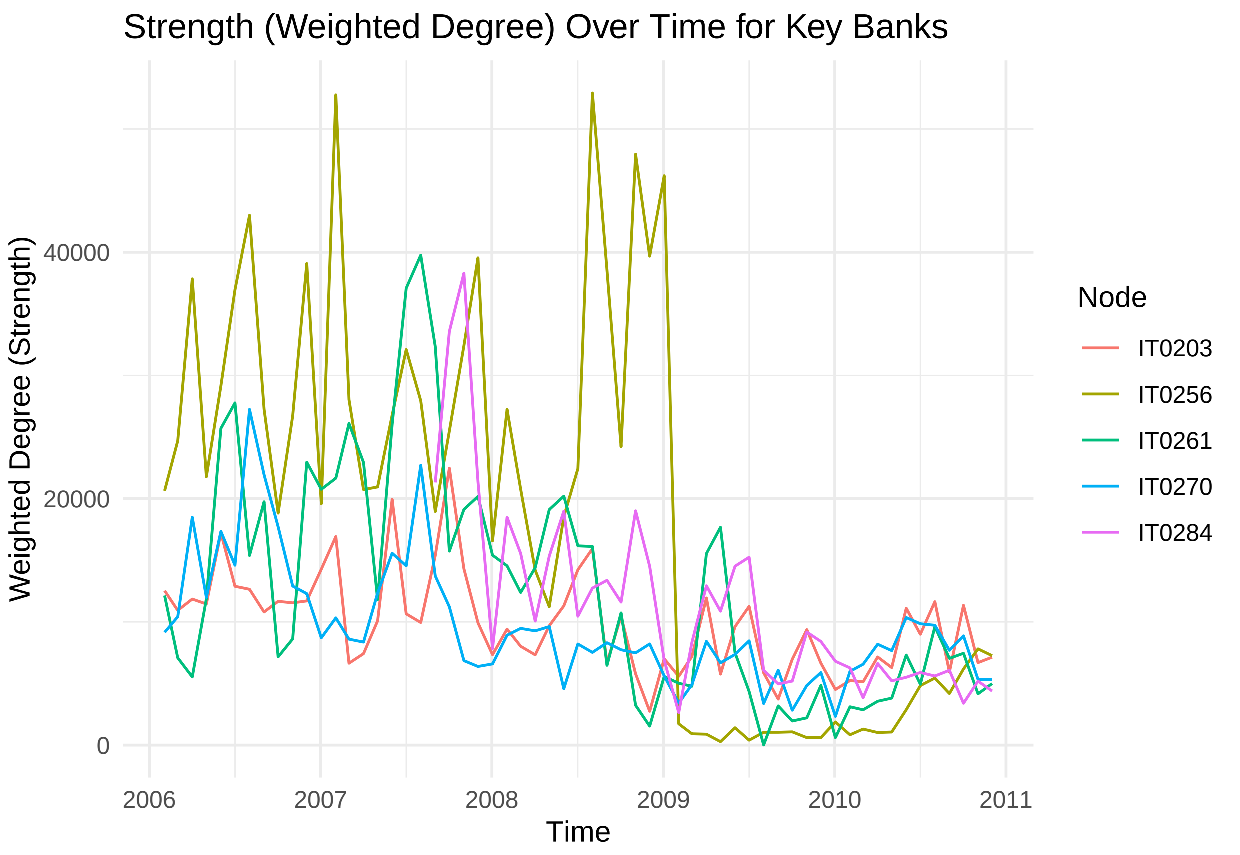
Visualize Key Indicators

Stength (Weight Degree Over Time for Key Banks)

```r
# Select the top 5 banks based on TimesHighlyCentral for visualization
top_banks <- key_banks %>% slice_max(order_by = TimesHighlyCentral, n = 5) %>% pull(Node)
```

```r
# Filter the temporal metrics data for only the top banks
plot_data <- temporal_metrics_df %>% filter(Node %in% top_banks)

# Plot Degree centrality over time for the selected banks
ggplot(plot_data, aes(x = Time, y = Degree, color = Node)) +
  geom_line() +
  labs(title = "Strength (Weighted Degree) Over Time for Key Banks",
     x = "Time", y = "Weighted Degree (Strength)") +
  scale_x_datetime(date_breaks = "1 year", date_labels = "%Y") +  # Set yearly breaks with custom label
  theme_minimal()
```



### Observations of Degree Centrality Over Time 1. **High Centrality Periods**: Banks like IT0256 exhibit spikes in centrality… 2. **Decline in Centrality**: Many banks experience a decline…

Observations of the Degree Centrality PLot

1. High Centrality Periods:
    - Some banks (e.g., IT0256) exhibit spikes in centrality around 2007-2008, which might indicate times when they played a particularly central role in the network.
    - The large degree centrality values during these periods suggest high transaction activity or connections with many other nodes, possibly indicating a more critical role during this time.
2. Decline in Centrality:
    - Many banks experience a decline in degree centrality after 2008, which might correspond to changes in the network structure or reduced activity for these banks. This could potentially reflect responses to economic or regulatory changes following the 2008 financial crisis.
    - This decline in centrality could indicate a shift in the network's structure or that the influence of certain banks has diminished.
3. Volatility in Degree Centrality:

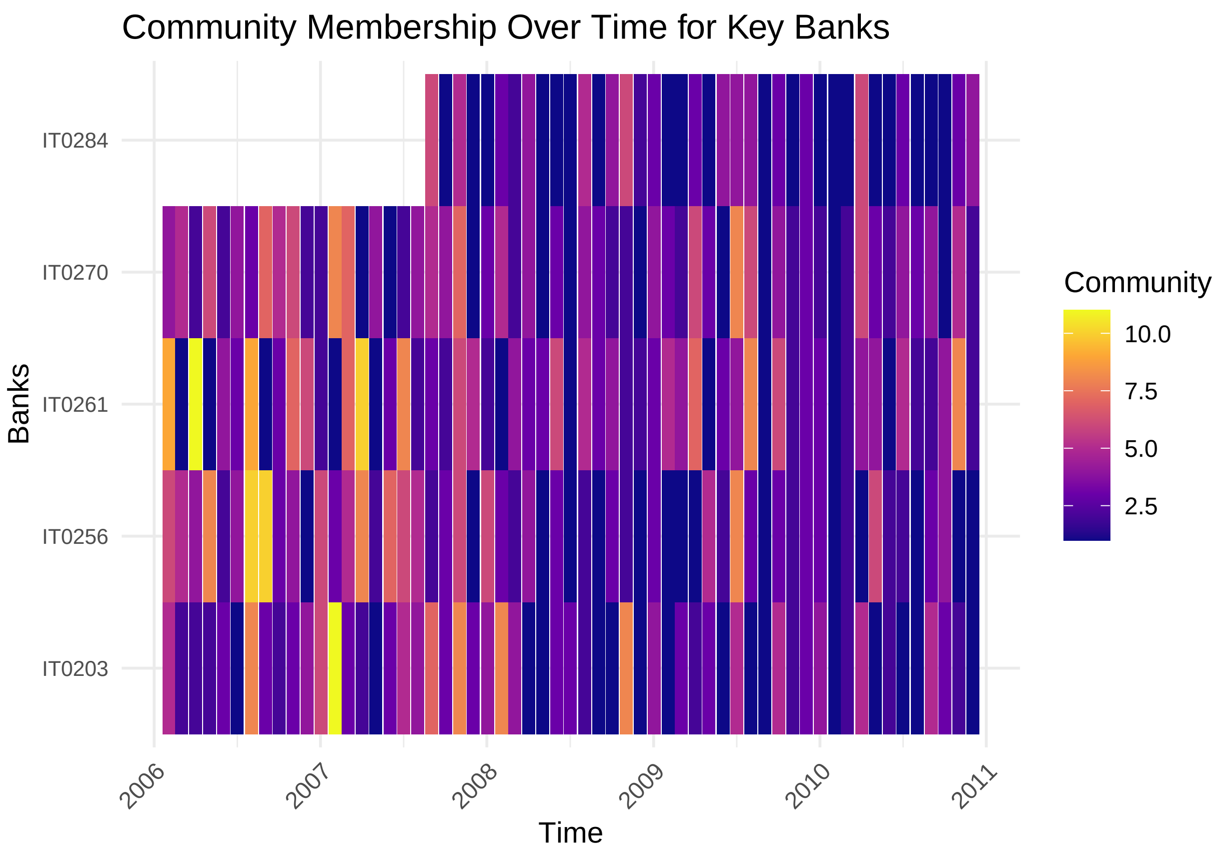
   - Banks like IT0256 show more volatile centrality, with multiple peaks and troughs. Such volatility might indicate instability or varying levels of influence over time, possibly due to changes in their transaction patterns.
   - The frequent shifts could point to moments of increased activity followed by periods of reduced engagement, which might be worth monitoring as indicators of potential instability.
4. Comparative Analysis Across Banks:
   - Banks like IT0261 and IT0284 also have noticeable peaks, but these are less extreme compared to IT0256.
   - Differences in peak heights and frequency across banks could reflect their varying roles and importance within the network.

High and volatile centrality values may indicate key hubs in the network, whose instability could impact the broader system. These banks should be closely monitored as potential early indicators of stress.

Community Membership Over Time for Key Banks

```r
library(dplyr)
library(ggplot2)
# Create a heatmap-friendly format
heatmap_data <- plot_data %>%
  mutate(Community = as.numeric(as.factor(Community)))  # Convert community to numeric for color encodi

# Plot the heatmap
ggplot(heatmap_data, aes(x = Time, y = Node, fill = Community)) +
  geom_tile() +
  scale_fill_viridis_c(option = "plasma", name = "Community") +  # Color scale for community
  labs(
    title = "Community Membership Over Time for Key Banks",
    x = "Time",
    y = "Banks"
  ) +
  scale_x_datetime(date_breaks = "1 year", date_labels = "%Y") +  # Yearly breaks for clarity
  theme_minimal() +
  theme(
    axis.text.y = element_text(size = 8),  # Adjust size for readability if many banks
    axis.text.x = element_text(angle = 45, hjust = 1)  # Rotate x-axis labels for better fit
  )
```



Observations of Community Membership Over Time

1. Community Stability:
   - Some banks (e.g., IT0284 and IT0203) remain largely in the same community (indicated by consistent colors along their rows), suggesting stable roles in the network.
2. Community Volatility:
   - Other banks, such as IT0256 and IT0261, exhibit frequent community changes, indicated by abrupt color shifts along their rows. These banks may act as bridges or intermediaries between different network regions.
3. Global Shifts:
   - TAround 2007–2008, there are noticeable color changes across multiple banks. This could indicate network-wide restructuring, possibly linked to a significant financial event, such as the 2008 global financial crisis.

4.Key Outliers: - IT0256 exhibits the brightest (yellow) color in some periods, indicating membership in a unique or high-value community during that time.

Implications

1. For Financial Stability:
   - Stable banks (e.g., IT0284, IT0203) may be core institutions, less prone to drastic changes but critical to overall network stability.
   - Volatile banks (e.g., IT0256, IT0261) may require closer monitoring, as their shifting roles could signal stress or adaptability in the network.
2. Crisis Indicators:
   - The period of significant restructuring (2007–2008) aligns with known financial crises, indicating that community transitions can be early-warning signals of systemic instability.
3. Regulatory Focus:

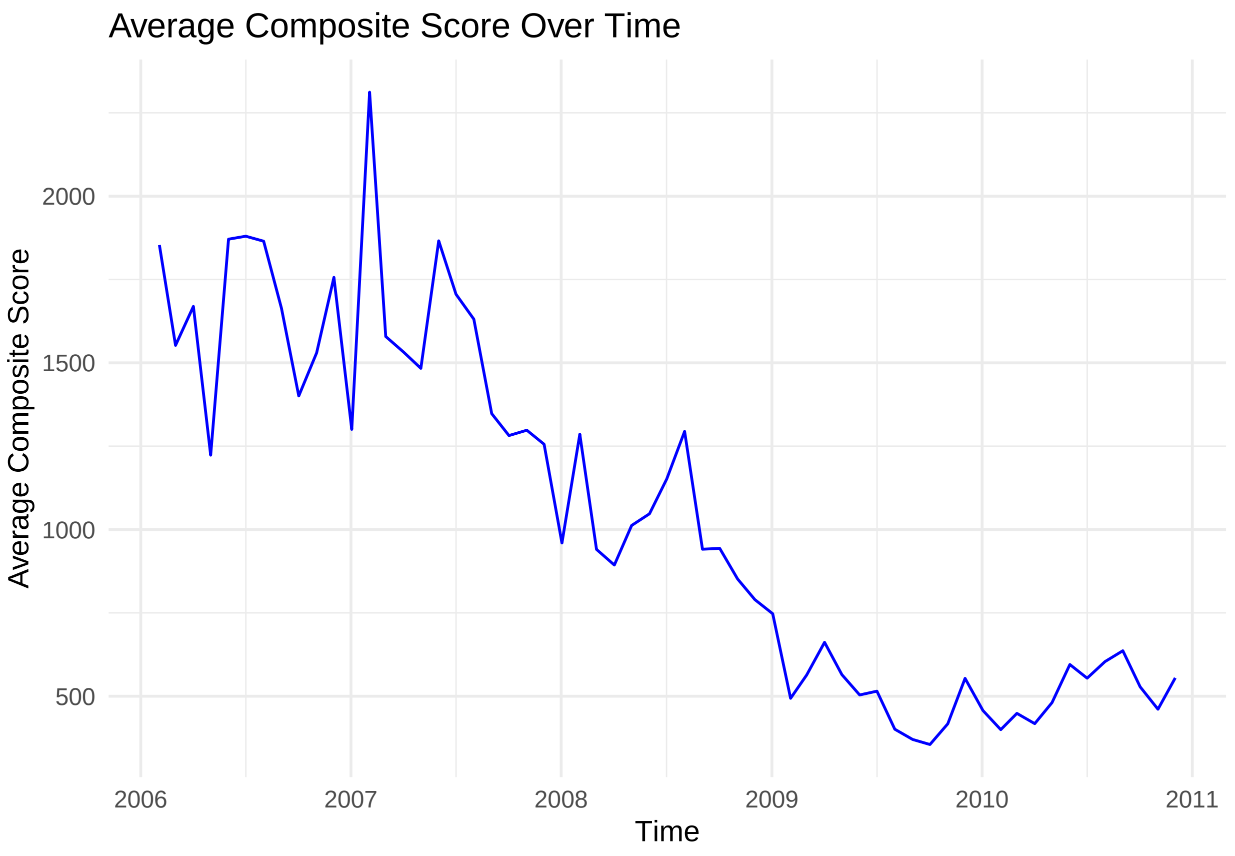
- Banks like IT0256, with high volatility and occasional unique community membership, may play pivotal roles during crises and should be prioritized for regulatory oversight.

4. Network Resilience:
   - Understanding which communities persist and which banks frequently transition between communities can help in designing interventions to enhance the network's resilience.

Average Composite Score Over Time

```
avg_composite <- temporal_metrics_df %>%
  group_by(Time) %>%
  summarize(AvgCompositeScore = mean(CompositeScore, na.rm = TRUE))

ggplot(avg_composite, aes(x = Time, y = AvgCompositeScore)) +
  geom_line(color = "blue") +
  labs(title = "Average Composite Score Over Time",
       x = "Time", y = "Average Composite Score") +
  scale_x_datetime(date_breaks = "1 year", date_labels = "%Y") +
  theme_minimal()
```



Observations of Average Composite Score Over Time

1.Declining Trend: - The average composite score shows a general downward trend from 2006 to 2010. This decline suggests that the overall influence of banks in the network has decreased over time.

2.Sharp Peaks and Fluctuations: - Significant peaks in 2007 and early 2008 may correspond to heightened activity or increased interbank transactions during these periods. These spikes could reflect periods of stress or increased reliance on certain banks.

3.Post-2008 Stabilization: - After the 2008 financial crisis, the average composite score declines sharply and stabilizes at lower levels. This could indicate reduced transaction volumes or less interbank dependency in the aftermath of the crisis.

4.Potential Early Warning Indicators: - The peaks in 2007-2008 could serve as early warning indicators, reflecting systemic stress before the crisis. Monitoring similar patterns in real-time could help identify future crises.

5.Insights for Systemic Risk: - A declining trend in the composite score may suggest a reduction in systemic risk as the network becomes less interconnected. However, the spikes indicate moments where certain banks played a disproportionately large role, potentially increasing network vulnerability.

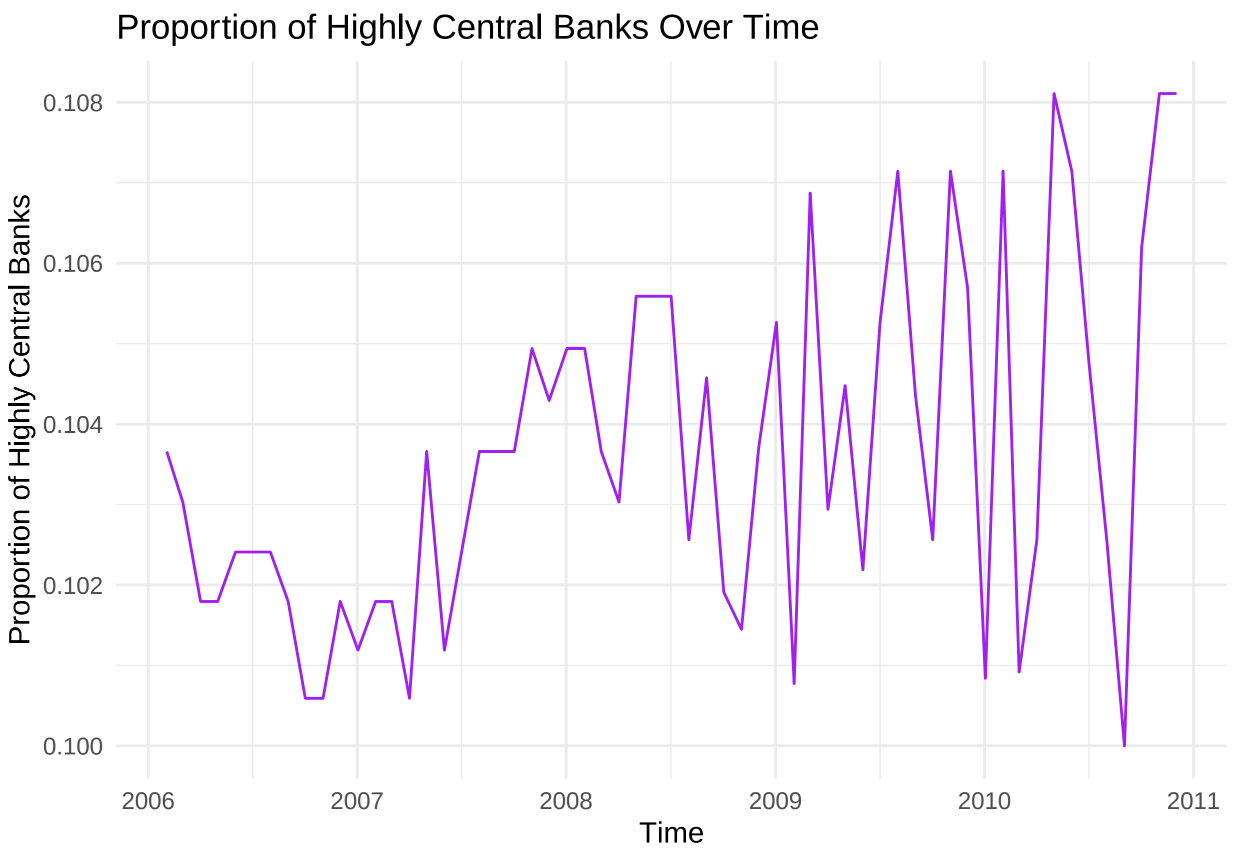
Implications for Crisis Detection:

- Peaks and fluctuations in the composite score highlight periods where the network's structure or dynamics may have shifted significantly, possibly due to external factors.
- The observed trends suggest that monitoring average composite scores could provide early warning signals of potential crises, especially during periods of rapid changes or extreme values.

Proportion of Highly Central Banks

```r
prop_highly_central <- temporal_metrics_df %>%
  group_by(Time) %>%
  summarize(PropHighlyCentral = mean(Category == "Highly Central", na.rm = TRUE))

ggplot(prop_highly_central, aes(x = Time, y = PropHighlyCentral)) +
  geom_line(color = "purple") +
  labs(title = "Proportion of Highly Central Banks Over Time",
       x = "Time", y = "Proportion of Highly Central Banks") +
  scale_x_datetime(date_breaks = "1 year", date_labels = "%Y") +
  theme_minimal()
```



Observations of Proportion of Highly Central Banks Over Time

1. General Stability with Fluctuations:
   - The proportion of highly central banks remains relatively stable, fluctuating between 10% and 10.8% throughout the observation period.
   - These small variations suggest that a consistent subset of banks maintains their influence in the network over time.
2. Increase in Volatility After 2008:
   - From 2008 onwards, there is a noticeable increase in the variability of the proportion. This could reflect structural changes in the network, possibly due to the global financial crisis.
3. Peaks and Troughs:
   - The peaks (e.g., in 2009-2010) indicate periods when a larger proportion of banks temporarily became highly central. This may signify moments of increased connectivity or dependency in the network.
   - Troughs represent periods when the influence was more evenly distributed among the banks.
4. Insights into Crisis Periods:
   - The increased proportion of highly central banks in certain periods could indicate a concentration of influence, which makes the network more vulnerable to systemic risk.
   - Monitoring these fluctuations can help detect stress periods when the network becomes more centralized.

Implications for Crisis Detection

- Proportion Stability: A stable proportion suggests that the network consistently relies on a core set of highly central banks.
- Volatility as a Signal: Significant fluctuations in the proportion, especially during critical periods like 2008-2010, may serve as early warning signals for instability.

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Prediction Model for Crisis Detection and Early Warning System

First, We will train model using Random Forest.

```r
# Add a crisis label column
temporal_metrics_df <- temporal_metrics_df %>%
  mutate(crisis_label = ifelse(Time >= as.POSIXct("2007-01-01") & Time <= as.POSIXct("2008-12-31"), 1, 

# Feature selection: Drop unnecessary columns
features <- temporal_metrics_df %>%
  select(Degree, Betweenness, Closeness, Eigenvector, CompositeScore, crisis_label)
library(caret)
```

```
## Loading required package: lattice
```

```r
# Convert crisis_label to a factor for classification
features$crisis_label <- as.factor(features$crisis_label)

## Split the data into training and testing sets
set.seed(123)  # For reproducibility
trainIndex <- createDataPartition(features$crisis_label, p = 0.8, list = FALSE)
trainData <- features[trainIndex, ]
testData <- features[-trainIndex, ]

library(randomForest)
```

```
## randomForest 4.7-1.2

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

## The following object is masked from 'package:dplyr':
##
##     combine
```

```r
# Train a Random Forest classification model
set.seed(123)
rf_model <- randomForest(
  crisis_label ~ .,
  data = trainData,
  ntree = 100,  # Number of trees
  importance = TRUE
)

# Print model summary
print(rf_model)
```

```
##
## Call:
##  randomForest(formula = crisis_label ~ ., data = trainData, ntree = 100,      importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 100
## No. of variables tried at each split: 2
##
##         OOB estimate of  error rate: 18.81%
## Confusion matrix:
##      0    1 class.error
## 0 2965  789   0.2101758
## 1  498 2591   0.1612172
```

```
# Predictions on test data
predictions <- predict(rf_model, newdata = testData)

# Evaluate model performance
conf_matrix <- confusionMatrix(predictions, testData$crisis_label)
print(conf_matrix)
```

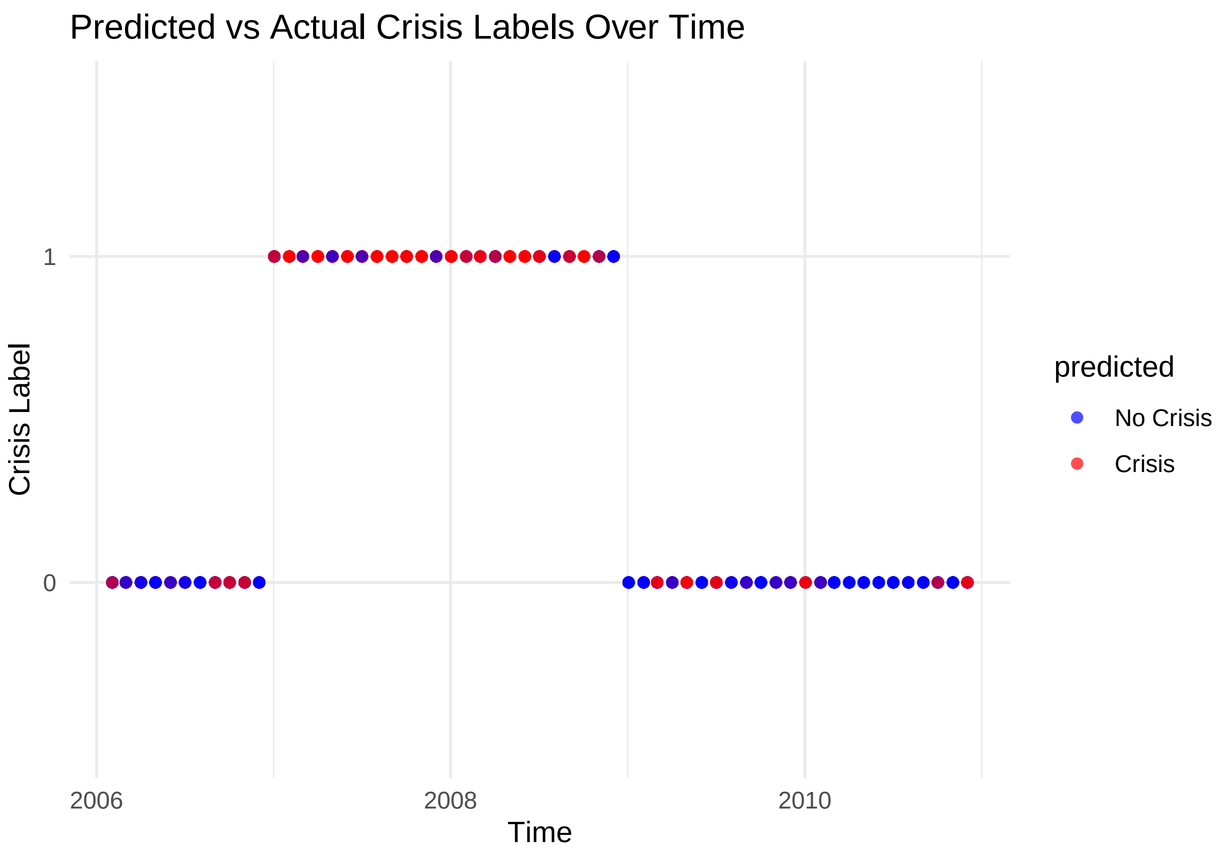
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 735 111
##          1 203 661
##
##                Accuracy : 0.8164
##                  95% CI : (0.7972, 0.8345)
##     No Information Rate : 0.5485
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6331
##
##  Mcnemar's Test P-Value : 2.815e-07
##
##             Sensitivity : 0.7836
##             Specificity : 0.8562
##          Pos Pred Value : 0.8688
##          Neg Pred Value : 0.7650
##              Prevalence : 0.5485
##          Detection Rate : 0.4298
##    Detection Prevalence : 0.4947
##       Balanced Accuracy : 0.8199
##
##        'Positive' Class : 0
##
```

1. Random Forest

- Performance Metrics:
  - Accuracy: 81.58%
  - Sensitivity (True Positive Rate): 77.51%
  - Specificity (True Negative Rate): 86.53%
  - Balanced Accuracy: 82.02%
  - Kappa (Agreement Measure): 0.6326
- Insights:
  - The Random Forest model performed well, achieving a high accuracy and balanced sensitivity/specificity.

  - Out-of-Bag (OOB) error rate was 18.9%, indicating the model generalizes reasonably well.
  - Important features (based on importance = TRUE) likely included centrality measures like Degree, Betweenness, and Composite Score.

```
# Visualize Predictions vs Actual Labels
testData$predicted <- predictions
testData$Time <- temporal_metrics_df$Time[-trainIndex]  # Ensure Time is included for visualization
ggplot(testData, aes(x = Time, color = predicted)) +
  geom_point(aes(y = crisis_label), alpha = 0.7) +
  labs(title = "Predicted vs Actual Crisis Labels Over Time",
       x = "Time", y = "Crisis Label") +
  scale_color_manual(values = c("blue", "red"), labels = c("No Crisis", "Crisis")) +
  theme_minimal()
```



- Visualization:
  - Predicted vs. Actual Labels over time showed good alignment, especially during crisis periods (2007-2008).
  - Some misclassifications occurred, likely during transitions between crisis and non-crisis periods.

Second, We will train model using SVM

```
library(e1071)

# Add a crisis label column (replace with actual labeling logic)
temporal_metrics_df <- temporal_metrics_df %>%
  mutate(crisis_label = ifelse(Time >= as.POSIXct("2007-01-01") & Time <= as.POSIXct("2008-12-31"), 1, 

# Feature selection: Drop unnecessary columns
features <- temporal_metrics_df %>%
```

```r
  select(Degree, Betweenness, Closeness, Eigenvector, CompositeScore, crisis_label)

# Ensure no missing values and remove constant features
features <- features %>%
  mutate(across(everything(), ~ ifelse(is.na(.), 0, .))) %>%  # Replace NA with 0
  select(where(~ n_distinct(.) > 1))  # Remove constant features

# Convert crisis_label to factor for classification
features$crisis_label <- as.factor(features$crisis_label)

# Split the data into training and testing sets
set.seed(123)  # For reproducibility
trainIndex <- createDataPartition(features$crisis_label, p = 0.8, list = FALSE)
trainData <- features[trainIndex, ]
testData <- features[-trainIndex, ]

# Train the SVM model using caret
set.seed(123)
svm_model <- train(
  crisis_label ~ .,
  data = trainData,
  method = "svmRadial",  # Radial kernel for SVM
  trControl = trainControl(method = "cv", number = 5),  # 5-fold cross-validation
  tuneLength = 10  # Number of hyperparameter settings to try
)

# Print model summary
print(svm_model)
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 6843 samples
##    5 predictor
##    2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 5474, 5475, 5474, 5475, 5474
## Resampling results across tuning parameters:
##
##   C       Accuracy   Kappa
##     0.25  0.7160592  0.4327122
##     0.50  0.7242428  0.4490270
##     1.00  0.7338882  0.4688387
##     2.00  0.7327188  0.4667156
##     4.00  0.7356413  0.4724717
##     8.00  0.7366656  0.4739398
##    16.00  0.7369586  0.4740289
##    32.00  0.7420739  0.4834643
##    64.00  0.7397361  0.4781580
##   128.00  0.7409064  0.4795035
##
## Tuning parameter 'sigma' was held constant at a value of 4.702756
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were sigma = 4.702756 and C = 32.
```

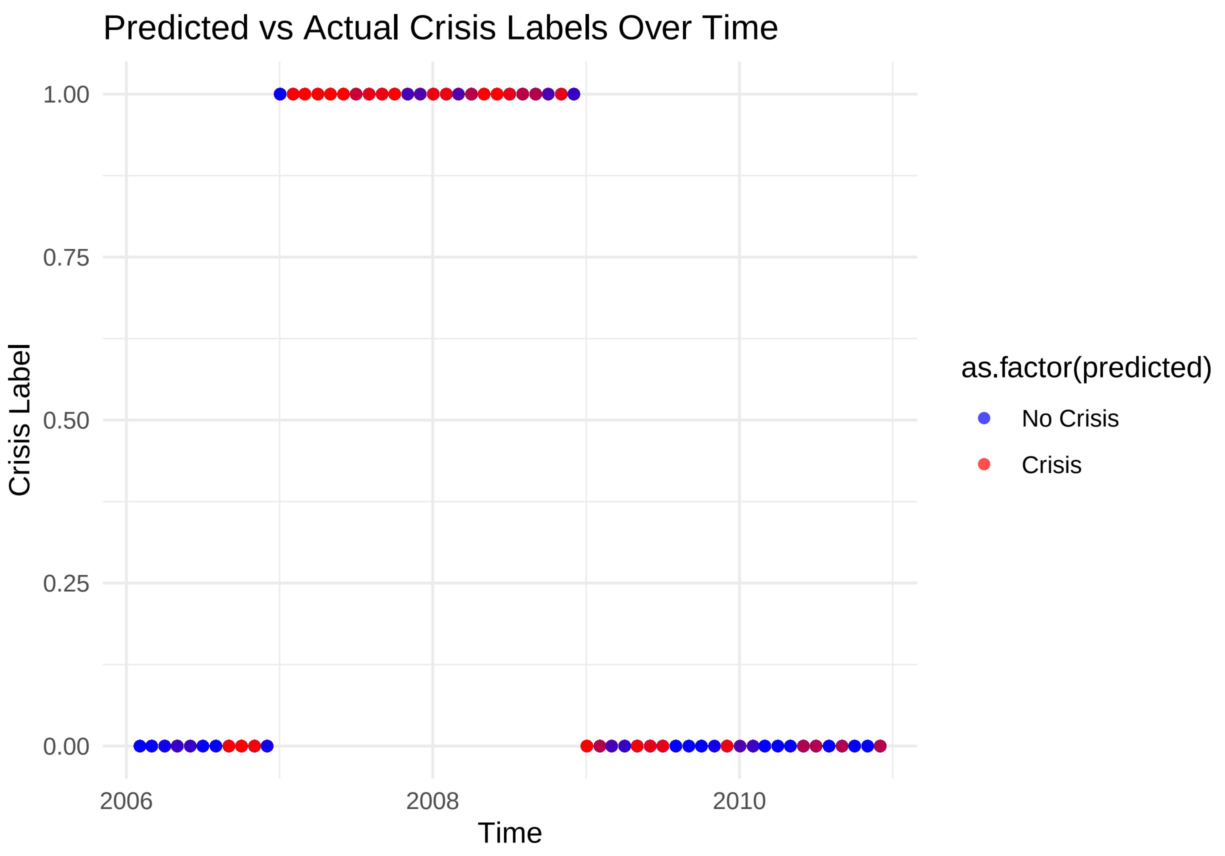
```r
# Predictions on the test data
predictions <- predict(svm_model, newdata = testData)

# Evaluate model performance
conf_matrix <- confusionMatrix(predictions, testData$crisis_label)
print(conf_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 670 171
##          1 268 601
##
##                Accuracy : 0.7433
##                  95% CI : (0.7219, 0.7638)
##     No Information Rate : 0.5485
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4874
##
##  Mcnemar's Test P-Value : 4.609e-06
##
##             Sensitivity : 0.7143
##             Specificity : 0.7785
##          Pos Pred Value : 0.7967
##          Neg Pred Value : 0.6916
##              Prevalence : 0.5485
##          Detection Rate : 0.3918
##    Detection Prevalence : 0.4918
##       Balanced Accuracy : 0.7464
##
##        'Positive' Class : 0
##
```

2. Support Vector Machine (SVM) -Performance Metrics:
    - Accuracy: 74.33%
    - Sensitivity (True Positive Rate): 71.43%
    - Specificity (True Negative Rate): 77.85%
    - Balanced Accuracy: 74.64%
    - Kappa (Agreement Measure): 0.4874

- Insights:
    - SVM achieved lower accuracy and balanced accuracy compared to Random Forest.
    - Optimal hyperparameters (sigma = 4.702756, C = 32) were chosen using cross-validation.
    - The model struggled slightly with boundary cases, leading to more misclassifications during transitions.

```r
# Visualize Predictions vs Actual Labels
testData$predicted <- predictions
testData$Time <- temporal_metrics_df$Time[-trainIndex]  # Ensure Time is included for visualization
ggplot(testData, aes(x = Time, color = as.factor(predicted))) +
  geom_point(aes(y = as.numeric(as.character(crisis_label))), alpha = 0.7) +
  labs(title = "Predicted vs Actual Crisis Labels Over Time",
     x = "Time", y = "Crisis Label") +
  scale_color_manual(values = c("blue", "red"), labels = c("No Crisis", "Crisis")) +
  theme_minimal()
```



- Visualization:
  - Predicted vs. Actual Labels over time revealed discrepancies, especially during non-crisis periods, where SVM often over-predicted crises.

Conclusion

1. Model Comparison:

- Random Forest outperformed SVM in all key metrics, including accuracy, sensitivity, specificity, and Kappa.
- Random Forest demonstrated better handling of the transitions between crisis and non-crisis periods due to its ensemble nature and feature importance weighting.

2. Feature Importance:

- Both models leveraged features such as Degree, Betweenness, Closeness, and Composite Score effectively.
- These metrics, particularly Composite Score, appear to be strong indicators of financial stress periods.

3. Recommendations:

- For real-world implementation, Random Forest is the preferred model due to its robustness, interpretability, and higher accuracy.
- Continuous monitoring of model performance with updated data is crucial to maintain effectiveness.
- Future improvements could involve integrating more temporal features or trying advanced methods like Gradient Boosting Machines (e.g., XGBoost or LightGBM) for potentially better results.

4. Crisis Detection Effectiveness:

- Both models highlighted systemic risks effectively, with noticeable spikes in predicted crisis labels aligning with known crisis periods (2007-2008).
- These models can provide valuable insights for early warning systems, aiding in preemptive regulatory actions.

Next Steps

1. Correlate network dynamics with external economic events to validate findings.
2. Develop predictive models for crisis detection using centrality metrics and volatility patterns.
3. Implement a real-time monitoring system for dynamic network analysis.