MRM Governance Framework

Model Risk Management (MRM) is a critical component of risk management of financial and non-financial risks. It involves the governance, development, validation, and monitoring of models used for risk assessment, decision-making, and regulatory compliance.

This notebook provides a summary of MRM governance framework for various risks, including financial and non-financial risks. It includes key steps, templates, and links to relevant guidelines such as SR11-7, OCC guidelines, Dodd-Frank, and Basel III.

Summary MRM Governance Steps:

1. **Establish MRM Governance Structure**
    - **Define Roles and Responsibilities**: Clearly outline the roles and responsibilities of the MRM team, including model developers, validators, users, and senior management.
    - **Governance Committee**: Form an MRM governance committee to oversee the framework and ensure compliance with regulatory requirements.
2. **Develop MRM Policies and Procedures**
    - **Policy Document**: Create a comprehensive MRM policy document that outlines the framework, objectives, and scope.
    - **Procedures**: Develop detailed procedures for model development, validation, implementation, and monitoring.
3. **Model Inventory and Classification**
    - **Model Inventory**: Maintain an inventory of all models, including their purpose, risk classification, and ownership.
    - **Risk Classification**: Classify models based on their risk levels (e.g., low, medium, high) according to SR11-7 and OCC guidelines.
4. **Model Development Standards**
    - **Development Guidelines**: Establish standards for model development, including data quality, assumptions, and methodologies.
    - **Documentation**: Ensure all models are thoroughly documented, including

assumptions, data sources, and validation results.

5. **Model Validation**
   - **Validation Process**: Implement a robust validation process to ensure models are accurate, reliable, and fit for purpose.
   - **Validation Templates**: Create standard templates for model validation reports, including sections for model description, validation methodology, results, and conclusions.
6. **Risk Assessment and Mitigation**
   - **Risk Assessment**: Conduct regular risk assessments to identify and mitigate risks associated with models.
   - **Mitigation Strategies**: Develop strategies to mitigate identified risks, such as enhanced validation, more frequent monitoring, or model replacement.
7. **Monitoring and Reporting**
   - **Ongoing Monitoring**: Implement ongoing monitoring of models to detect any changes in performance or risk levels.
   - **Reporting Templates**: Create standard reporting templates for regular updates to senior management and the board, aligning with FERC-NERC and other regulatory requirements.
8. **Internal Audit and Compliance**
   - **Internal Audit**: Conduct regular internal audits to assess the effectiveness of the MRM framework.
   - **Compliance Checks**: Regularly check for compliance with FERC-NERC, SR11-7, OCC guidelines, Dodd-Frank, and Basel III.
9. **Training and Awareness**
   - **Training Programs**: Develop training programs for staff involved in model risk management to ensure they are aware of the policies, procedures, and best practices.
   - **Awareness Campaigns**: Conduct awareness campaigns to educate all relevant stakeholders about the importance of model risk management.
10. **Technology and Tools**
    - **MRM Software**: Consider implementing specialized software for model risk management to streamline processes and enhance efficiency.

- **Data Management**: Ensure robust data management practices to support accurate and reliable model outputs.

11. **Continuous Improvement**
    - **Feedback Loop**: Establish a feedback loop to continuously improve the MRM framework based on lessons learned and changing regulatory requirements.
    - **Benchmarking**: Benchmark against industry best practices and regulatory expectations to ensure the framework remains robust and effective.

Standard Templates for MRM:

1. **Model Development Template**
    - **Purpose**: Document the purpose and scope of the model.
    - **Assumptions**: List all assumptions made during model development.
    - **Data Sources**: Detail the data sources used in the model.
    - **Methodology**: Describe the methodology and algorithms used.
2. **Model Validation Template**
    - **Model Description**: Provide a brief description of the model, including its purpose, scope, and key features.
    - **Validation Methodology**: Detail the validation methodology used, including statistical tests, back-testing, and sensitivity analysis.
    - **Results**: Present the validation results, including any discrepancies or issues identified during the validation process.
    - **Conclusions**: Summarize the conclusions and recommendations based on the validation results, highlighting any areas for improvement or further investigation.
3. **Risk Assessment Template**
    - **Risk Identification**: Identify potential risks associated with the model, such as data quality issues, model assumptions, and external factors.
    - **Risk Analysis**: Analyze the likelihood and impact of identified risks, using qualitative and quantitative methods.
    - **Mitigation Strategies**: Outline strategies to mitigate identified risks, such as enhanced validation, more frequent monitoring, or model replacement.
    - **Monitoring Plan**: Describe the monitoring plan to ensure ongoing risk management, including key performance indicators (KPIs) and reporting frequency.

4. **Reporting Template**
    - **Executive Summary**: Provide a high-level summary of the model's performance and risk status, including key findings and recommendations.
    - **Detailed Analysis**: Include detailed analysis of model performance, validation results, and risk assessment findings.
    - **Performance Metrics**: Present key performance metrics and benchmarks to evaluate the model's effectiveness.
    - **Compliance Status**: Summarize the model's compliance with regulatory requirements and internal policies.
    - **Recommendations**: Provide actionable recommendations for improving model performance, risk management, and compliance.

Sample Complex Credit Risk Models Template

1. Model Identification

- Model Name:
- Model ID:
- Model Owner:
- Date of Development:

2. Purpose and Scope

- Purpose of the Model:
- Scope of the Model:

3. Assumptions

- List of Assumptions:
    - Default rates follow a Poisson distribution.
    - Recovery rates are constant over time.
    - Economic conditions remain stable.

4. Data Sources

- Internal Data:
- External Data:

5. Methodology

- Statistical Methods:

    - Logistic Regression, Survival Analysis.

6. Validation Results

- Validation Date:
- Validation Method: Back-testing, Stress-testing.
- Results:

7. Risk Classification

- Risk Level:
- Justification:

8. Monitoring and Reporting

- Monitoring Frequency: Quarterly
- Reporting Frequency: Monthly
- Performance Metrics:
    - Default Rate (PD): {pd_value}
    - Loss Given Default (LGD): {lgd_value}
    - Expected Loss (EL): {expected_loss}
    - CreditVaR (95% confidence): {credit_var}
    - Accuracy: {accuracy}
    - ROC AUC Score: {roc_auc}
    - Brier Score: {brier}

9. Mitigation Strategies

- Enhanced Validation: Annual re-validation.
- Frequent Monitoring: Monthly performance reviews.
- Model Replacement: Consider alternative models if performance deteriorates.

10. Interpretability

- SHAP Values: {shap_values}

11. Thresholds and Alerts

- Thresholds:
    - Accuracy: 0.8
    - ROC AUC Score: 0.7
    - Brier Score: 0.2
- Alerts: {alerts}

12. Conclusions and Recommendations

- Action Plan for Remediation of Identified Issues

```
# Sample data
data = {
    'credit_score': [650, 700, 750, 600, 800, 720, 680, 740, 660, 710, 670, 730, 69
    'income': [50000, 60000, 70000, 45000, 80000, 65000, 55000, 72000, 48000, 62000
    'loan_amount': [100000, 150000, 200000, 80000, 250000, 180000, 120000, 220000,
    'default': [0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0]
}

df = pd.DataFrame(data)

# Features and target
X = df[['credit_score', 'income', 'loan_amount']]
y = df['default']

# Handle imbalanced data using SMOTE
if len(y[y == 1]) < 5:
    X_res, y_res = X, y
else:
    smote = SMOTE(random_state=42, k_neighbors=min(5, len(y[y == 1])))
    X_res, y_res = smote.fit_resample(X, y)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.3, ra

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train the model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)[:, 1]

# Metrics
conf_matrix = confusion_matrix(y_test, y_pred)
accuracy = accuracy_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)
brier = brier_score_loss(y_test, y_pred_proba)

# Additional metrics: PD, LGD, CreditVaR
```

```python
# Additional metrics: PD, LGD, CreditVaR
pd_value = y_pred_proba.mean()
lgd_value = 0.5  # Assuming a constant LGD for simplicity
expected_loss = pd_value * lgd_value
credit_var = norm.ppf(0.95, loc=expected_loss, scale=np.std(y_pred_proba * lgd_valu

# Interpretability using SHAP
explainer = shap.Explainer(model, X_train)
shap_values = explainer(X_test)

# Monitoring and Thresholds
thresholds = {
    'accuracy': 0.8,
    'roc_auc': 0.7,
    'brier': 0.2
}

# Check if metrics are within thresholds
metrics = {
    'accuracy': accuracy,
    'roc_auc': roc_auc,
    'brier': brier
}

alerts = {}
for metric, value in metrics.items():
    if value < thresholds[metric]:
        alerts[metric] = f"{metric} is below the threshold ({thresholds[metric]}).
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:379: Unde
  warnings.warn(
```

Sample Operational Risk MRM Template

1. Model Identification

- Model Name: Operational Risk Metrics Model
- Model ID: ORM-001
- Model Owner: Risk Management Department
- Date of Development: [Insert Date]

2. Purpose and Scope

- Purpose of the Model: To quantify and manage operational risks, ensuring compliance with regulatory requirements and internal policies.

- Scope of the Model: Covers all operational risk events, including internal fraud, external fraud, employment practices, workplace safety, clients, products, and business disruption.

3. Assumptions

- List of Assumptions:
  - Historical data represents future operational risk events.
  - Frequency and severity of operational risk events follow a known distribution.
  - Model parameters are stable over the analysis period.

4. Data Sources

- Data Source 1:
  - Description: Internal incident reports
  - Frequency of Update: Monthly
- Data Source 2:
  - Description: External industry benchmarks
  - Frequency of Update: Quarterly
- Data Source 3:
  - Description: Regulatory filings
  - Frequency of Update: Annually

5. Methodology

- Description of Methodology: The model uses historical data to estimate the frequency and severity of operational risk events, employing statistical methods to calculate key risk metrics.

Operational Risk Metrics Calculation

- The model calculates key operational risk metrics such as Value at Risk (VaR), Conditional Value at Risk (CFVaR), and Earnings at Risk (EaR).

6. Validation Plan

- Validation Methodology: Back-testing, stress testing, and sensitivity analysis.
- Validation Frequency: Semi-annually
- Validation Criteria: Accuracy of risk estimates, alignment with regulatory requirements, and consistency with internal policies.

7. Model Performance Metrics

- Key Performance Indicators (KPIs):
    - Number of operational risk incidents
    - Average severity of incidents
    - Compliance with regulatory requirements
- Risk Metrics:
    - Cash Flow Value at Risk (CFVaR)
    - Earnings at Risk (EaR)
    - Operational Risk Capital (ORC)

8. Risk Assessment

- Potential Risks:
    - Data quality issues
    - Model parameter instability
    - Regulatory changes
- Likelihood and Impact of Each Risk:
    - Data quality issues: High likelihood, High impact
    - Model parameter instability: Medium likelihood, High impact
    - Regulatory changes: Low likelihood, High impact
- Risk Score (Likelihood x Impact):
    - Data quality issues: 9
    - Model parameter instability: 6
    - Regulatory changes: 4

9. Mitigation Strategies

- Mitigation Strategy for Data quality issues: Implement data validation processes and regular audits.
- Mitigation Strategy for Model parameter instability: Conduct regular model recalibration and parameter updates.
- Mitigation Strategy for Regulatory changes: Stay updated with regulatory changes and adapt the model accordingly.

10. Monitoring Plan

- Monitoring Frequency: Quarterly

- Monitoring Methods: Regular reviews of incident reports, performance metrics, and regulatory compliance.
- Responsible Parties: Risk Management Department, Compliance Department

11. Compliance with Regulations

- Compliance with Basel III:
  - Specific Requirements Met: Operational Risk Capital (ORC) calculation, stress testing, and scenario analysis.
  - Compliance Checklist:
    - [ ] ORC calculation methodology
    - [ ] Stress testing procedures
    - [ ] Scenario analysis documentation
- Compliance with Other Relevant Regulations:
  - Specific Requirements Met: Internal controls and risk management practices as per local regulatory bodies.
  - Compliance Checklist:
    - [ ] Internal control framework
    - [ ] Risk management policies
    - [ ] Regular audits and reviews

12. Conclusions and Recommendations

- Summary of Conclusions for quantifying and managing operational risks that ensures compliance with regulatory requirements and internal policies.
- Recommendations for Remediation Actions and Model Improvement

```
# Sample data: Historical operational risk losses
# Replace this array with real data
losses = np.array([100, 150, 200, 250, 300, 350, 400, 450, 500, 550])

# Function to calculate Value at Risk (VaR)
def calculate_var(losses, alpha):
    """
    Calculate Value at Risk (VaR) at a given confidence level.

    Parameters:
    losses (array-like): Historical operational risk losses.
    alpha (float): Confidence level (e.g., 0.05 for 95% confidence).
```

```
    Returns:
    float: Value at Risk at the given confidence level.
    """
    return np.percentile(losses, (1 - alpha) * 100)


# Function to calculate CFaR (ES)
  def calculate_cfar(losses, alpha):
    excess_returns = returns[returns < var]
    cvar = np.mean(excess_returns)
    return cvar

# Function to calculate Cash Flow at Risk (CFaR)
def calculate_cfar(losses, alpha):
    """
    Calculate Cash Flow at Risk (CFaR) at a given confidence level.

    Parameters:
    losses (array-like): Historical operational risk losses.
    alpha (float): Confidence level (e.g., 0.05 for 95% confidence).

    Returns:
    float: Cash Flow at Risk at the given confidence level.
    """
    var = calculate_var(losses, alpha)
    return np.mean(losses[losses > var])

# Function to calculate Earnings at Risk (EaR)
def calculate_ear(earnings, var):
    """
    Calculate Earnings at Risk (EaR) based on earnings and Value at Risk (VaR).

    Parameters:
    earnings (float): Earnings of the company.
    var (float): Value at Risk at the given confidence level.

    Returns:
    float: Earnings at Risk.
    """
    return earnings * var

# Parameters
alpha = 0.05  # 95% confidence level
earnings = 10000  # Example earnings (replace with real data)
```

Key Performance Metrics:

Market Value at Risk (VaR)

$$\text{VaR}_{\alpha} = \text{percentile}(\text{losses}, (1 - \alpha) \times 100)$$

VaR at a confidence level α is the value below which a specified percentage of returns fall. For example, a 95% VaR means there is a 5% chance that the loss will exceed this value.

Conditional Value at Risk (ES)

$$\text{CVaR}_{\alpha} = \text{mean}(\text{losses} > \text{VaR}_{\alpha})$$

CFaR is the expected loss given that the loss exceeds the VaR threshold. It provides a measure of the severity of losses beyond the VaR level.

Cash Flow Value at Risk(CFVaR)

$$\text{VaR}_{\alpha}(X) = \inf\{x \in \mathbb{R} : P(X \leq x) \geq \alpha\}$$

This represents the threshold below which the cash flow will fall with a probability of α. One can also report the worst negative cash flow.

Earnings at Risk (EaR)

$$\text{EaR} = \text{earnings} \times \text{VaR}$$

EaR quantifies the potential impact of market risk on a company's earnings. It is calculated as the product of the company's earnings and the VaR.

Liquidity Risk Metrics

- Liquidity Coverage Ratio (LCR):

  $$\text{LCR} = \frac{\text{High-Quality Liquid Assets (HQLA)}}{\text{Total Net Cash Outflows over 30 days}}$$

This is the ratio of high-quality liquid assets to total net cash outflows over a 30-day period.

- Net Stable Funding Ratio (NSFR):

  $$\text{NSFR} = \frac{\text{Available Stable Funding}}{\text{Required Stable Funding}}$$

NSFR assesses the availability of stable funding relative to the amount of required stable funding over a one-year period. It ensures that banks have a stable funding profile.

Credit Risk Metrics:

- **Probability of Default (PD)**

$$\text{PD} = \frac{\text{Number of Defaults}}{\text{Total Number of Obligors}}$$

PD is the likelihood that a borrower will default on their debt obligations.

- **Loss Given Default (LGD)**

$$\text{LGD} = \frac{\text{Total Loss}}{\text{Total Exposure at Default}},$$

LGD measures the proportion of the exposure that is lost when a default occurs.

- **Expected Loss (EL)**

$$\text{EL} = \text{PD} \times \text{LGD} \times \text{Exposure at Default (EAD)}$$

EL is the expected amount of loss given the probability of default, the loss given default, and the exposure at default.

- **Unexpected Loss (UL)**

$$\text{UL} = \text{Standard Deviation of Losses} \times \text{Z-score}$$

UL represents the variability of losses around the expected loss. It is calculated as the product of the standard deviation of losses and the Z-score corresponding to the desired confidence level.

- **Brier Score =** $\frac{1}{N} \sum_{i=1}^{N} (f_i - o_i)^2$

where f_i is the forecast probability, o_i is the observed outcome (1 for event occurrence, 0 otherwise), and N is the number of predictions.

Brier Score is a measure of the accuracy of probabilistic predictions. It ranges from 0 to 1, where 0 indicates perfect accuracy and 1 indicates the worst possible accuracy.

Conclusion

This notebook serves as an illustration of the MRM (Model Risk Management) framework. As models develop, it is crucial to recognize the variety of risks that organizations face. These risks can be categorized into several types, each requiring specific models and methodologies for effective management:

1. **Operational Risks**: These include internal fraud, external fraud, employment practices, workplace safety, client-related issues, product risks, and business disruptions. Operational risk models focus on quantifying and managing these risks to ensure smooth operations and minimize potential losses.
2. **Market Risks**: These involve fluctuations in market conditions that can affect an organization's financial performance. Market risk models, such as Value at Risk (VaR) and Conditional Value at Risk (CVaR), help in assessing the potential impact of market movements on the organization's earnings.
3. **Credit Risks**: These relate to the likelihood of borrowers defaulting on their debt obligations. Credit risk models evaluate the probability of default (PD), loss given default (LGD), and expected loss (EL), providing insights into the creditworthiness of borrowers and the potential financial impact of defaults.
4. **Liquidity Risks**: These pertain to an organization's ability to meet its short-term and long-term financial obligations. Liquidity risk models, such as the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), ensure that organizations have sufficient liquid assets to cover their cash outflows and maintain financial stability.
5. **Model Risks**: These arise from the use of models in risk management and decision-making processes. Model risk management involves validating, monitoring, and updating models to ensure their accuracy and reliability. This includes back-testing, stress testing, and sensitivity analysis to assess the performance and robustness of the models.

By addressing these various types of risks through specialized models and methodologies, the MRM framework helps organizations stay compliant with regulatory requirements and internal policies. Regular updates and continuous monitoring are essential to keep the framework effective and relevant in a dynamic risk landscape.