1. *VaR*

**Notes** Bachelor degree

1. *CAPM*

**Source**: https://en.wikipedia.org/wiki/Capital\_asset\_pricing\_model

1. *BS*

**Slides Citi**

1. *Greeks*

**Source**: https://en.wikipedia.org/wiki/Greeks\_(finance)

1. *Derivatives (equity, interest, FX)*

**Slides Citi**

1. *Credit and Counterparty Risk (PD, LGD, EAD etc)*

**Slides Citi**

1. *Liquidity risk*

**Source**: https://www.bis.org/publ/bcbs165.pdf

Łukasz Filar

1. ***Pierwsza****: Dlaczego chcesz do nas dołączyć? itp. Ile szmalu?*

***Dlaczego:*** *Nowe wyzwania, ciekawa oferta, chęć poznania nowych obszarów.*

***Szmal:*** *B2B: 18-20k*

1. ***Druga****: z szefem zespołu z Krakowa. Co robiłeś w karierze?*

- Dili: aktuariat, modelowanie w ub na zycie, sprawdzanie istniejących modeli

- CS: stress testing, regresyjne modele makro P&L banku plus Assets, głównie R

- AAA: programowanie dla zakldow modeli cashflow

- JPM: modele regresyjne stress testing, modele szeregow czasowych do prognozowania BAU

1. ***Trzecia:*** *techniczna. dejtasajentist.:*
2. *Masz zbiór danych i jak po kolei przeprowadzasz analizę.*

**1. Collecting Data:**

As you know, machines initially learn from the data that you give them. It is of the utmost importance to collect reliable data so that your machine learning model can find the correct patterns. The quality of the data that you feed to the machine will determine how accurate your model is. If you have incorrect or outdated data, you will have wrong outcomes or predictions which are not relevant.

Make sure you use data from a reliable source, as it will directly affect the outcome of your model. Good data is relevant, contains very few missing and repeated values, and has a good representation of the various subcategories/classes present.

**2. Preparing the Data:**

After you have your data, you have to prepare it. You can do this by :

* Putting together all the data you have and randomizing it. This helps make sure that data is evenly distributed, and the ordering does not affect the learning process.
* Cleaning the data to remove unwanted data, missing values, rows, and columns, duplicate values, data type conversion, etc. You might even have to restructure the dataset and change the rows and columns or index of rows and columns.
* Visualize the data to understand how it is structured and understand the relationship between various variables and classes present.
* Splitting the cleaned data into two sets - a training set and a testing set. The training set is the set your model learns from. A testing set is used to check the accuracy of your model after training.

1. *Co robisz z missingami i outlierami.*

Missing data:

* Deleting Rows with missing values
* Impute missing values for continuous variable (mean / median)
* Impute missing values for categorical variable (most frequent category)
* Other Imputation Methods
* Using Algorithms that support missing values
* Prediction of missing values
* Imputation using Deep Learning Library — Datawig

**Source**: <https://towardsdatascience.com/7-ways-to-handle-missing-values-in-machine-learning-1a6326adf79e>

1. *Jak robisz exploratory data analysis.*

1.Load .csv files

2.Dataset Information

3.Data Cleaning/Wrangling:

the process of cleaning and unifying messy and complex data sets for easy access and analysis.

4.Group by names

5.Summary of Statistics

6. Dealing with Missing Values

7. Skewness and kurtosis

8. Categorical variable

9. Create Dummy Variables

10. Removing Columns

11.Univariate Analysis: “Uni” +“Variate” Univariate, means one variable or feature analysis. The univariate analysis basically tells us how data in each feature is distributed. just sample as below.

12. Bivariate Analysis: “Bi” +“Variate” Bi-variate, means two variables or features are analyzed together, that how they are related to each other. Generally, we use to perform to find the relationship between the dependent and independent variable. Even you can perform this with any two variables/features in the given dataset to understand how they related to each other.

13.Multi-Variate Analysis: means more than two variables or features are analyzed together. that how they are related to each other.

14.Distributions of the variables/features.

15.Correlation – By Heatmap the relationship between the features.

Source: https://www.analyticsvidhya.com/blog/2021/04/rapid-fire-eda-process-using-python-for-ml-implementation/

1. *Jak po kolei budujesz model.*

* Problem Definition
* Data Collection
* Data Preparation
* Data Visualization
* ML Modeling
* Feature Engineering
* Model Deployment

**Source**: https://medium.com/@datadrivenscience/7-stages-of-machine-learning-a-framework-33d39065e2c9

1. *Jak uniknąć overfittingu przy algorytmach ML.*

* Cross-validation. Cross-validation is a powerful preventative measure against overfitting. Train with more data. It won't work every time, but training with more data can help algorithms detect the signal better. ...
* Remove features. ...
* Early stopping. ...
* Regularization. ...
* Ensembling

**Source**: https://elitedatascience.com/overfitting-in-machine-learning

1. *Jak weryfikujesz model.*

* Confusion matrix.
* Accuracy.
* Precision.
* Recall.
* Specificity.
* F1 score.
* Precision-Recall or PR curve.
* ROC (Receiver Operating Characteristics) curve.

**Source**: https://towardsdatascience.com/various-ways-to-evaluate-a-machine-learning-models-performance-230449055f15

1. *Zalety i wady różnych metod weryfikacji modelu.*

**Source**: <https://towardsdatascience.com/various-ways-to-evaluate-a-machine-learning-models-performance-230449055f15>

1. *Na trzecim etapie też trzeba było napisać jakieś proste kody i u mnie pseudokod wystarczał. Język: R/Python/inny*

**Source**: https://medium.com/pythoneers/7-must-know-algorithms-for-your-next-coding-interview-26252748b895

1. ***Czwarta:*** *też techniczna, ale bardziej ogólna:*
2. *Gauss-Markov (autokorelacja, heteroskedastyczność i ich konsekwencje)*

**Source**: https://www.sidmartinbio.org/what-are-the-implications-of-the-gauss-markov-assumptions/

1. *Bias-variance trade-off*

**Source**: https://www.analyticsvidhya.com/blog/2020/08/bias-and-variance-tradeoff-machine-learning/

1. *Do czego służą wykresy reszt modelu,*

**Source**: https://towardsdatascience.com/how-to-use-residual-plots-for-regression-model-validation-c3c70e8ab378

1. *Kolejne pytania z diagnostyki modelu czyli jakie testy do czego służą i co nam mówią.*

Autocorrelation: ACF/PACF, Breusch-Godfrey test, Ljung-Box

Heteroskedasticity: Breusch-Pagan

Normality: Jarque-Berra, Shapiro-Wilk, QQ plot

Stationarity: KPSS, DL-GLS, ADF, regression against time

(\*) Seasonality: Kruskal-Wallis

Linearity: Significance of power 2,3,4,… of the regressors

1. *Różnica między confidence i prediction interval.*

https://www.statology.org/confidence-interval-vs-prediction-interval/

1. *Podstawy modeli autoregresyjnych i modeli VAR.*

<https://online.stat.psu.edu/stat501/lesson/14/14.1>

<https://online.stat.psu.edu/stat510/lesson/11/11.2>

1. *Musiałem też napisać kilka prostych funkcji i jeden algorytm.*

<https://www.interviewbit.com/algorithm-interview-questions/>

1. *Miałem też opowiedzieć o tym jak sobie radzę ze stresem, jaki styl pracy lubię, co bym doradził swojemu obecnemu szefowi i jakieś "funny story"...*
2. *O VaR mnie nie pytali gdyż aplikowałem do credit risku, ale miałem pytania odnośnie wyceny opcji, VaR i ES gdy przychodziłem do HSBC i nie było wiadomo do jakiego zespołu się dostanę. Z wyceny te pytania jednak były bardzo proste więc nie przyjmowałbym się nimi choć z drugiej strony to było wtedy stanowisko juniorskie*

**PYTHON – JPM:**

1. Bubble sort – co to jest?
2. Projekty: przykłady
3. Struktury danych – wymień
4. Różnica między queue a stack … ?
5. Lambda function
6. Jak zbudować klasę w Pythonie?
7. Jak zainicjować klasę?
8. Co robi self?
9. Czym jest decorator?
10. Co to jest list comprehension?
11. Co się stanie jak weźmiesz z array [-1] indeks?
12. Chyba coś o zip function…?
13. Właściwości Pythona jako języka OOP …? Co to jest inheritance?
14. Pytanie o Git. Jak stworzyć branch? Komenda
15. Multithread vs multiprocess

<https://data-flair.training/blogs/top-python-interview-questions-answer/>

Financial Engineering:

1. Put-call parity
2. Ito Lemma

**FRTB**

* **Standard Approach**

*The Standard Approach (SA) in the Fundamental Review of the Trading Book (FRTB) is a method for calculating market risk capital charges for banks that is part of the Basel III regulatory framework. The SA replaces the previous standardized method for calculating market risk capital charges, which was criticized for not adequately capturing risk.*

*Under the SA, banks are required to calculate the market risk capital charge using a combination of two different methodologies:* ***the sensitivity-based approach (SBA) and the default risk charge (DRC).***

*The* ***SBA*** *measures the potential loss in the value of a portfolio due to changes in market factors, such as interest rates, equity prices, and foreign exchange rates. It does so by calculating the delta and the vega of each position in the portfolio. Delta measures the change in the value of a position for a unit change in the underlying market factor, while vega measures the change in the value of a position for a unit change in the implied volatility of the underlying market factor. The SBA then applies a stress scenario to these sensitivities and calculates the resulting loss.*

*The* ***DRC*** *measures the potential loss due to default risk, which is the risk that a counterparty will default on a transaction. It does so by multiplying the notional amount of each transaction by a credit spread that reflects the creditworthiness of the counterparty. The DRC also applies a stress scenario to these credit spreads to calculate the resulting loss.*

*The SA also includes a specific* ***risk add-on (SRA)*** *that captures risks that are not captured by the SBA and the DRC. The SRA applies to positions that have specific risks, such as concentration risk, event risk, and liquidity risk. The SRA is calculated as a percentage of the net notional amount of the specific risk positions in the portfolio.*

* **Internal Model**

*In addition to the Standard Approach (SA), the Fundamental Review of the Trading Book (FRTB) also allows banks to use internal models to calculate market risk capital charges. Internal models are proprietary models developed by banks that aim to capture the specific risk profile of their trading activities.*

*Under the FRTB, banks must meet strict requirements in order to use internal models, including demonstrating their models' accuracy, data integrity, and robustness to regulators. Banks that use internal models must also comply with strict reporting and validation requirements.*

*Examples of models that can be applied internally by banks in FRTB capital charge calculations include:*

*Value-at-Risk (VaR) models: VaR models estimate the potential loss that a portfolio could experience within a specified time period at a given level of confidence. VaR models can be calibrated to capture specific market risk factors, such as interest rate risk, equity risk, and foreign exchange risk.*

*Historical Simulation models: Historical Simulation models use historical market data to simulate the distribution of potential losses that a portfolio could experience. Historical Simulation models can be used to capture non-linear and extreme market risk events that may not be captured by VaR models.*

*Stressed VaR models: Stressed VaR models apply a specific stress scenario to a VaR model to estimate the potential loss that a portfolio could experience under extreme market conditions. Stressed VaR models can be used to capture tail risk events that may not be captured by regular VaR models.*

*Incremental Risk Charge (IRC) models: IRC models estimate the incremental risk of adding a new position to an existing portfolio. IRC models can be used to capture the risk of illiquid or complex positions that may not be captured by traditional market risk models.*

*Expected Shortfall (ES) models: ES models estimate the expected loss of a portfolio beyond the VaR limit. ES models can be used to capture tail risk events and are often preferred by regulators over VaR models.*

*Overall, internal models allow banks to capture their specific risk profile more accurately than the Standard Approach (SA), but they require significant resources and expertise to develop, validate, and maintain.*

* **VaR / ES**

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*Overall, internal models allow banks to capture their specific risk profile more accurately than the Standard Approach (SA), but they require significant resources and expertise to develop, validate, and maintain.*

*To simulate the risk factors of equity prices, interest rates, and foreign exchange rates, we would typically use stochastic models that are calibrated to historical market data. Here are some commonly used simulation processes for each of these risk factors:*

***Equity prices****: Equity prices can be modeled using stochastic processes such as the* ***Black-Scholes model, the Heston model, or the Jump Diffusion model.*** *These models can simulate the path of equity prices over time based on assumptions about the underlying volatility, interest rates, and other factors that affect equity prices.*

***Interest rates****: Interest rates can be modeled using stochastic processes such as the Hull-White model, the* ***Cox-Ingersoll-Ross (CIR)*** *model, or the* ***Vasicek*** *model. These models can simulate the path of interest rates over time based on assumptions about the level of interest rates, the volatility of interest rates, and the mean reversion of interest rates.*

***Foreign exchange rates****: Foreign exchange rates can be modeled using stochastic processes such as the* ***Garman-Kohlhagen*** *model or the* ***Heston*** *model with stochastic volatility. These models can simulate the path of foreign exchange rates over time based on assumptions about the underlying volatility, interest rates, and other factors that affect foreign exchange rates.*

*Once the simulation processes have been specified, we would typically use Monte Carlo simulation to generate a large number of scenarios for each risk factor. These scenarios would be used to estimate the risk parameters of the risk model, such as the volatilities and correlations of the market risk factors. We would then use the estimated parameters to calculate the portfolio risk measures, such as* ***Value-at-Risk (VaR)*** *and* ***Expected Shortfall (ES).***

*It is worth noting that the specific simulation processes used may vary depending on the bank's internal modeling practices and the regulatory requirements in their jurisdiction. Additionally, the simulation processes would need to be validated and tested to ensure that they accurately capture the risk of the portfolio.*

* **Liquidity Horizon**

*The liquidity horizon refers to the period of time over which a bank is able to liquidate a given trading position in an orderly manner without incurring significant market impact costs. The concept of liquidity horizon is used in the FRTB to determine the capital charge for market risk, which is based on the potential losses that a bank could incur over a certain holding period.*

*Under the FRTB, banks are required to calculate the expected shortfall (ES) of their trading book positions, which represents the potential loss beyond a certain confidence level over a given holding period. The holding period depends on the liquidity horizon of the positions, which is determined based on the characteristics of the instruments and the market conditions.*

*For example, a liquid instrument such as a stock listed on a major exchange may have a liquidity horizon of one day, meaning that the bank can assume that it can liquidate the position without significant market impact over that period. On the other hand, an illiquid instrument such as a distressed debt security may have a liquidity horizon of several months, meaning that the bank may need to hold the position for a longer period of time to avoid incurring significant market impact costs.*

*The liquidity horizon plays a key role in determining the capital charge for market risk under the FRTB, as it affects the holding period and the corresponding ES calculation. By taking into account the liquidity of the positions and the market conditions, the FRTB aims to provide a more risk-sensitive and forward-looking framework for market risk capital requirements.*

* **Default Risk Charge**

*The Default Risk Charge (DRC) is an important component of the market risk capital charge under the Fundamental Review of the Trading Book (FRTB) framework. The DRC is designed to capture the potential losses that a bank may face due to the default of a counterparty on its trading book positions.*

*The DRC is calculated based on the expected loss (EL) and unexpected loss (UL) components of counterparty credit risk. The EL represents the expected loss due to the default of a counterparty over a one-year period, while the UL represents the potential loss beyond the EL at a certain confidence level.*

*The DRC is calculated as the sum of the EL and UL components of counterparty credit risk, multiplied by a factor that reflects the risk of the counterparty. The factor is determined based on the credit rating of the counterparty and the maturity of the positions.*

*The DRC is applied to all trading book positions that are subject to counterparty credit risk, including derivatives, securities financing transactions, and repo transactions. The DRC is intended to provide a more risk-sensitive measure of counterparty credit risk than the previous regulatory framework, which relied on a standardized approach that did not take into account the specific characteristics of the positions and counterparties.*

*The inclusion of the DRC in the market risk capital charge under the FRTB framework reflects the increased focus on counterparty credit risk in the post-crisis regulatory environment. By requiring banks to hold additional capital to cover potential losses due to counterparty default, the FRTB aims to enhance the resilience of the financial system and reduce the risk of contagion in the event of a counterparty default.*

*Which models would you apply to estimate Default Risk Charge?*

*There are various models that can be applied to estimate the Default Risk Charge (DRC) under the Fundamental Review of the Trading Book (FRTB) framework. Some of the commonly used models are:*

*Credit rating-based approach: This approach uses the credit rating of the counterparty to determine the DRC. The DRC is calculated as a percentage of the notional amount of the positions, based on the credit rating of the counterparty.*

*Internal ratings-based (IRB) approach: This approach uses the bank's own estimates of the probability of default (PD) and loss given default (LGD) for each counterparty to calculate the DRC. The PD and LGD estimates are based on the bank's historical data and risk models.*

*Credit valuation adjustment (CVA) VaR approach: This approach estimates the DRC by incorporating the credit risk of the counterparty into the Value-at-Risk (VaR) calculation. The CVA VaR approach considers the potential losses due to counterparty credit risk over a specified holding period.*

*Monte Carlo simulation approach: This approach uses Monte Carlo simulation to estimate the potential losses due to counterparty default over a specified holding period. The simulation takes into account the credit quality of the counterparty and the characteristics of the positions.*

*Each of these approaches has its own strengths and weaknesses, and the choice of model depends on the specific requirements and characteristics of the bank's trading book. Banks are required to apply the approach that is most appropriate for their trading book, based on the size and complexity of the positions and the availability of data and risk models.*

* **Non Modellable Risk Factors**

*Non-Modellable Risk Factors (NMRFs) are risk factors that cannot be modeled using parametric models, and are therefore subject to a separate NMRF charge under the Fundamental Review of the Trading Book (FRTB) framework. The NMRF charge is intended to cover the potential losses due to risk factors that cannot be accurately modeled using standard statistical techniques.*

*To account for NMRFs, banks are required to identify and quantify the risk associated with each NMRF in their trading book. This can be done using a combination of expert judgment, historical data analysis, and statistical techniques.*

*For exotic equities, banks may use scenario analysis or stress testing to assess the potential losses associated with these risk factors. This involves simulating the performance of the exotic equity in different market scenarios and assessing the impact on the portfolio. Banks may also use machine learning techniques to identify patterns and correlations in historical data that can inform their risk assessment.*

*For interest rate volatility, banks may use historical data analysis to identify the behavior of interest rate volatility under different market conditions. They may also use statistical techniques such as extreme value theory and copula models to estimate the tail risk associated with interest rate volatility.*

*For less liquid FX rates, banks may use scenario analysis or stress testing to assess the potential losses associated with these risk factors. They may also use market data analysis and expert judgment to assess the liquidity risk of the FX rates and incorporate this into their risk assessment.*

**Example: CDS**

*If a CDS is not a modellable risk factor (NMRF), then the capital risk charge for that CDS would be based on the Default Risk Charge (DRC) as per the FRTB guidelines. However, there are some ways to decrease the capital risk charge related to the CDS:*

*Reduce the notional amount of the CDS: The capital risk charge is directly proportional to the notional amount of the CDS. By reducing the notional amount, the capital risk charge can be lowered.*

*Hedge the CDS with modellable risk factors: If the CDS can be hedged with modellable risk factors such as equity or interest rate futures, the capital risk charge for the CDS can be reduced by offsetting the risk with these modellable factors.*

*Use proxy hedging: If the CDS cannot be hedged with modellable risk factors, a proxy hedge can be used instead. A proxy hedge involves using a similar instrument that is modellable to hedge the risk of the CDS. This can reduce the capital risk charge for the CDS.*

*Reduce the tenor of the CDS: The capital risk charge is directly proportional to the tenor of the CDS. By reducing the tenor, the capital risk charge can be lowered.*

* **Real price data**
* **Residual Risk Add On**

*The Residual Risk Add-On (RRAO) is a component of the market risk capital charge under the Fundamental Review of the Trading Book (FRTB) framework. The RRAO is intended to capture the risks associated with non-linear positions that are not adequately captured by the standard models used to calculate the Value-at-Risk (VaR) and Expected Shortfall (ES) metrics.*

*To calculate the RRAO, banks are required to perform a series of stress tests on their portfolio, which involve assessing the potential losses under extreme market conditions. The RRAO is then calculated as the maximum loss arising from these stress tests, subject to a minimum floor of 0.1% of the notional amount of the portfolio.*

*The RRAO can be calculated using either historical simulation or scenario analysis. In historical simulation, the bank simulates the performance of the portfolio using historical market data and assesses the losses under extreme market conditions. In scenario analysis, the bank constructs a set of hypothetical market scenarios and assesses the losses under each scenario.*

*The RRAO is calculated separately for each desk or trading book within the bank, and is added to the capital charge for each desk to arrive at the total market risk capital charge.*

*It is important to note that the RRAO is an additional capital charge that is applied on top of the standard VaR and ES metrics, and is intended to capture the residual risks associated with non-linear positions. By incorporating this additional capital charge, banks can better account for the potential losses associated with these positions and enhance the overall resilience of the financial system.*

* **Correlations**
* **VaR – historical, parametric, simulation based**
* **CASE: example of project with simulation / VaR / ES/ derivative pricing (e.g. Interest Rate Volatility modelling based on the Master Thesis and Jupyter Notebook swaption vol calibration)**

**Interest rate simulations:**

*One common approach to simulate the short-term interest rate, such as 3M EURIBOR, is to use a stochastic process model. One such model is the Vasicek model, which is a one-factor model that assumes the short-term interest rate follows a mean-reverting process. Here's an example of how to generate a simulated path of 3M EURIBOR using the Vasicek model:*

*Assume that the Vasicek model is defined as follows:*

*dr(t) = a(b - r(t))dt + σdW(t)*

*where:*

*r(t) is the short-term interest rate at time t*

*a, b, and σ are parameters that determine the behavior of the process*

*W(t) is a Wiener process or Brownian motion*

*Step 1: Choose parameter values*

*First, we need to choose appropriate values for the model parameters. Let's assume the following parameter values:*

*a = 0.1*

*b = 0.03*

*σ = 0.02*

*Step 2: Generate a sequence of random numbers*

*Next, we need to generate a sequence of random numbers that follow a standard normal distribution. Let's assume we want to simulate the path for a 1-year period with a time step of 1 day, which means we need to generate 365 random numbers.*

*Step 3: Use the Euler-Maruyama method to simulate the path*

*Finally, we can use the Euler-Maruyama method to simulate the path of the short-term interest rate. The method involves discretizing the stochastic differential equation and using the random numbers to generate a series of simulated values.*

*Let's assume that the initial short-term interest rate is r(0) = 0.02. Then, we can simulate the path for 1 year (365 days) as follows:*

*Choose a time step of Δt = 1/365*

*For each time step i, calculate the new interest rate as follows:*

*r(i) = r(i-1) + a(b - r(i-1))Δt + σΔt^(1/2)ε(i)*

*where ε(i) is the ith random number generated in Step 2*

*By repeating this process for each time step, we can generate a simulated path of the short-term interest rate.*

*Note that this is just one example of how to simulate the short-term interest rate using a stochastic process model. There are many other models and methods that can be used, depending on the specific requirements of the analysis.*

**Interest Rate Volatility modelling based on the Master Thesis and Jupyter Notebook swaption vol calibration**

XXX

**VaR for Equity Derivatives portfolio (Corporate)**

*Simulating Value at Risk (VaR) of a large portfolio of equity derivatives using sensitivities (delta and vega) and accounting for hedging limits can be a complex process, but here is a general framework:*

*Step 1: Calculate sensitivities*

*The first step is to calculate the sensitivities of each derivative in the portfolio with respect to the underlying equity index and volatility. The most common sensitivities used in VaR calculations are delta and vega. Delta measures the change in the price of the derivative for a small change in the price of the underlying asset, while vega measures the change in the price of the derivative for a small change in the implied volatility of the underlying asset.*

*Step 2: Simulate changes in equity index and volatility*

*Next, we need to simulate changes in the equity index and volatility. This can be done using a stochastic process model, such as the Heston model. The model generates random variables that can be used to simulate changes in the equity index and volatility over a given time horizon.*

*Step 3: Calculate changes in derivative prices*

*Using the sensitivities and simulated changes in equity index and volatility, we can calculate the change in price of each derivative in the portfolio. This step involves multiplying the sensitivities by the simulated changes in the equity index and volatility, respectively.*

*Step 4: Aggregate changes in derivative prices*

*Once we have calculated the change in price of each derivative in the portfolio, we need to aggregate these changes to obtain the overall change in the value of the portfolio. This can be done by summing the changes in price of all the individual derivatives.*

*Step 5: Calculate VaR*

*Finally, we can calculate the VaR of the portfolio by multiplying the aggregate change in the value of the portfolio by a certain confidence level. For example, a 95% VaR would be obtained by multiplying the aggregate change by 1.645 (the 95th percentile of a standard normal distribution).*

*In addition to the above steps, we need to account for hedging limits to ensure that the simulated changes in the equity index and volatility do not violate the limits. This can be done by setting up constraints on the simulated changes in the index and volatility and running a Monte Carlo simulation to generate a distribution of possible outcomes that respect the limits.*

*Overall, simulating VaR of a large portfolio of equity derivatives using sensitivities and hedging limits requires a sophisticated approach and careful consideration of the assumptions and limitations of the models and methods used.*

* **P&L attribution**

*The Profit and Loss (P&L) Attribution test is a key component of the Fundamental Review of the Trading Book (FRTB) framework, which is designed to ensure that banks hold adequate capital against market risk.*

*The P&L Attribution test is used to assess the accuracy of a bank's Value at Risk (VaR) model by comparing the actual daily P&L of the trading book to the P&L predicted by the VaR model. The test is performed on a daily basis over a one-year period, and the results are aggregated to determine if the VaR model is accurate enough to be used for regulatory capital purposes.*

*The P&L Attribution test involves the following steps:*

*Calculate the daily VaR using the bank's VaR model. This VaR is the expected maximum loss with a given probability over a one-day holding period.*

*Calculate the daily P&L of the trading book over the same one-day holding period.*

*Compare the actual daily P&L to the P&L predicted by the VaR model. If the actual P&L is within the VaR limit, then the VaR model is considered accurate for that day. If the actual P&L exceeds the VaR limit, then the VaR model is deemed inaccurate for that day.*

*Aggregate the results of the daily P&L Attribution tests over the one-year period to determine the overall accuracy of the VaR model. If the VaR model is deemed to be accurate enough, then the bank can use it for regulatory capital purposes.*

*The P&L Attribution test is important because it helps to ensure that banks are accurately measuring their market risk and holding enough capital to cover potential losses. It also provides a way to identify and correct any weaknesses in the VaR model, which can help to improve the accuracy of risk management and decision-making.*

* **Actual / Hypothetical / Risk Theoretical P&L**

*Actual P&L, Hypothetical P&L, and Risk Theoretical P&L are different ways of measuring the profit and loss (P&L) of a trading portfolio, each with a different purpose.*

***Actual P&L****: This is the actual profit or loss that a trader or portfolio manager realizes from their trading activities. It is the difference between the cost of the assets purchased and the proceeds from their sale, including any income generated from the assets, such as dividends or interest. Actual P&L is important for assessing the performance of the trader or portfolio manager.*

***Hypothetical P&L****: This is a simulated P&L that shows what the profit or loss would be if a trader had made different trading decisions. It is used to evaluate the impact of different trading strategies or scenarios on the portfolio's P&L. Hypothetical P&L can be generated using historical data or by running simulations using a variety of market scenarios.*

***Risk Theoretical P&L****: This is a measure of the potential P&L of a portfolio under different market scenarios, based on the risk factors that are relevant to the portfolio. It is used to evaluate the risk of the portfolio and to estimate the capital requirements under regulatory frameworks such as the Basel Accords. Risk Theoretical P&L is calculated by applying stress tests or Monte Carlo simulations to the portfolio's risk factors.*

*In summary, Actual P&L is the realized profit or loss from trading activities, Hypothetical P&L is a simulated P&L used to evaluate trading strategies, and Risk Theoretical P&L is a measure of potential P&L used for risk management and regulatory purposes.*

* **Backtesting**

*Backtesting is a process used in the Fundamental Review of the Trading Book (FRTB) to validate the accuracy and reliability of the internal models used for calculating the risk capital requirements for the trading book. The backtesting process involves comparing the model's expected performance with its actual performance over a specific period, typically one year.*

*The following are the key steps involved in the backtesting process in FRTB:*

*Select the backtesting period: The backtesting period should be selected to cover a period that is long enough to provide a meaningful evaluation of the model's performance but short enough to capture recent changes in the market conditions.*

*Determine the confidence level and holding period: The confidence level and holding period are determined based on the regulatory requirements and the bank's internal risk management policies. The confidence level represents the probability that the actual losses will not exceed the expected losses, and the holding period represents the time horizon over which the model is expected to perform.*

*Calculate the expected and actual P&L: The expected P&L is calculated using the internal model, and the actual P&L is calculated based on the actual market conditions and trading activities.*

*Compare the expected and actual P&L: The expected and actual P&L are compared to determine if the model's performance meets the regulatory and internal requirements. If the actual P&L exceeds the expected P&L at the chosen confidence level and holding period, it indicates that the model is underestimating the risk, and the model needs to be recalibrated or adjusted.*

*Perform root cause analysis: If the model's performance is found to be inadequate, the root cause of the issue should be identified and addressed. This may involve recalibrating the model or making changes to the risk management practices.*

*Report the results: The results of the backtesting process should be reported to the relevant stakeholders, including senior management and the regulatory authorities.*

*In summary, the backtesting process in FRTB is a critical component of model validation and involves comparing the expected and actual P&L to ensure the model is performing as expected and meets the regulatory and internal requirements.*

* **Kolmogorov test**

*The Kolmogorov-Smirnov (KS) test is a statistical test used in the P&L attribution test to determine whether the distribution of the model P&L is consistent with the distribution of the actual P&L. The KS test is a non-parametric test, which means that it does not require any assumptions about the underlying distribution of the P&L data.*

*The following are the key steps involved in using the KS test in the P&L attribution test:*

*Select the test period: The test period should be selected to cover a period that is long enough to provide a meaningful evaluation of the model's performance but short enough to capture recent changes in the market conditions.*

*Calculate the model and actual P&L: The model P&L is calculated using the internal model, and the actual P&L is calculated based on the actual market conditions and trading activities.*

*Compute the cumulative distribution function (CDF): The CDF is a function that shows the probability of observing a value less than or equal to a given value. The CDF is calculated for both the model P&L and the actual P&L.*

*Compare the CDFs: The KS test compares the CDFs of the model and actual P&L to determine if they are consistent with each other. If the CDFs are significantly different, it indicates that the model is not accurately capturing the underlying market conditions.*

*Compute the KS statistic: The KS statistic is a measure of the maximum distance between the two CDFs. A larger KS statistic indicates that the model and actual P&L are further apart, and the model is not accurately capturing the market conditions.*

*Compare the KS statistic with the critical value: The critical value is a threshold value that is determined based on the sample size and the significance level. If the KS statistic exceeds the critical value, it indicates that the model is not consistent with the actual P&L, and the model needs to be recalibrated or adjusted.*

*In summary, the KS test is used in the P&L attribution test to determine if the model P&L is consistent with the actual P&L. If the two distributions are significantly different, it indicates that the model is not accurately capturing the market conditions, and further analysis is required to identify the root cause of the issue.*

* **Spearman test (?)**
* **IMCC calculation**

IMCC (Incremental Default and Migration Risk Capital Charge) is a component of the capital charge calculation for counterparty credit risk under the Basel III framework. It measures the potential losses that a bank may incur due to the risk of default or migration of its counterparties. The IMCC calculation involves the following steps:

Select the exposure and determine its maturity: Assume that the bank has a derivative contract with a counterparty with a notional amount of $100 million and a maturity of 5 years.

Determine the rating of the counterparty: Assume that the counterparty is rated BB+ by a recognized rating agency.

Determine the probability of default (PD): Assume that the PD for the counterparty is 3%.

Calculate the expected loss (EL) due to default: EL = PD x EAD x LGD, where EAD (Exposure at Default) is the expected exposure at default and LGD (Loss Given Default) is the expected loss in case of default. Assume that the EAD is $10 million and the LGD is 50%. Therefore, EL = 3% x $10 million x 50% = $150,000.

Determine the migration risk: Migration risk is the risk that the counterparty's credit rating may deteriorate, resulting in a higher PD and a higher EL. Assume that the migration risk factor (MRF) for the counterparty is 0.5%.

Calculate the incremental EL due to migration risk: Incremental EL = MRF x PD x EAD x (1 - LGD). Therefore, incremental EL = 0.5% x 3% x $10 million x (1 - 50%) = $75,000.

Calculate the IMCC: IMCC = max(EL, incremental EL) - EL. Therefore, IMCC = max($150,000, $75,000) - $150,000 = $75,000.

In this example, the IMCC for the counterparty is $75,000, which represents the potential losses that the bank may incur due to the risk of default or migration of the counterparty. The IMCC is added to the other components of the capital charge to determine the total capital requirement for counterparty credit risk.

**Quant:**

* Stochastic process
* Filtration
* Arbitrage
* Risk neutral pricing
* Brownian motion
* Martingale / Markov
* Stationarity
* BS model / params / Greeks / assumptions
* Example of deriv, how to price, how Greeks evolve
* Vol smile
* PC parity / how to derive / what happens if does not hold
* MC simulation – how to perform / how many paths / discretization (grid) / how to account for correlation in BMs / how to calibrate parameters / how to test (Martingale test)
* Cholesky decomposition (matrix properties)
* Ito Lemma (Taylor series expansion)
* Chain Rule

**Modelling methods:**

* **Linear regression**
* **PCA**

*Principal Component Analysis (PCA) is a useful technique for modeling interest rates because it can help identify the underlying factors that are driving the changes in interest rates. Here are the steps that can be followed to apply PCA in modeling interest rates:*

*Collect data: Collect a time series of interest rates for a set of maturities. The maturities should be evenly spaced, such as 1-month, 3-month, 6-month, 1-year, etc.*

*Standardize the data: Calculate the log returns of the interest rates and standardize them by subtracting the mean and dividing by the standard deviation. This step is important to ensure that the PCA is based on the covariance matrix of the returns, rather than the levels of the interest rates.*

*Calculate the covariance matrix: Calculate the covariance matrix of the standardized log returns. This matrix represents the relationships between the different interest rates and their volatility.*

*Perform PCA: Perform PCA on the covariance matrix to identify the principal components. Each principal component represents a linear combination of the original interest rates, and the weights of the combination are the loadings of the principal component. The first principal component explains the most variance in the data, and subsequent principal components explain decreasing amounts of variance.*

*Determine the number of principal components: Determine the number of principal components to retain based on the percentage of variance explained. A common rule of thumb is to retain enough principal components to explain at least 80% of the total variance.*

*Calculate the factor loadings: Calculate the factor loadings for each principal component. The factor loadings represent the sensitivity of each interest rate to each principal component.*

*Simulate interest rates: Simulate interest rates based on the principal components and their factor loadings. This can be done by generating random numbers for each principal component and multiplying them by their respective factor loadings. The simulated interest rates will have the same covariance structure as the original interest rates, but with new levels and volatilities based on the simulated principal components.*

*By applying PCA in modeling interest rates, we can reduce the dimensionality of the problem and identify the underlying factors that are driving the changes in interest rates. This can be useful for risk management, hedging, and pricing of interest rate derivatives.*

* **Interpolation (linear, cubic splines)**
* **Jacobian**
* **SABR model (volatility)**
* **FFT**
* **Heston model**

*The Heston model is a popular stochastic volatility model that is commonly used to model the dynamics of asset prices, particularly in the context of option pricing. The model was introduced by Steven Heston in 1993 and is based on two stochastic differential equations (SDEs): one for the underlying asset price and one for the volatility.*

*The SDE for the asset price is given by:*

*dS(t) = rS(t)dt + sqrt(V(t))S(t)dW1(t)*

*where S(t) is the asset price at time t, r is the risk-free interest rate, V(t) is the stochastic volatility of the asset, and W1(t) is a Wiener process that represents the Brownian motion of the asset price.*

*The SDE for the volatility is given by:*

*dV(t) = κ(θ-V(t))dt + σ\*sqrt(V(t))dW2(t)*

*where V(t) is the instantaneous variance of the volatility process, κ is the rate at which the volatility reverts to its long-term mean, θ is the long-term mean of the volatility, σ is the volatility of the volatility process, and W2(t) is a Wiener process that represents the Brownian motion of the volatility.*

*The parameters κ, θ, σ, and the correlation ρ between the two Brownian motions W1 and W2 are estimated from historical data.*

*The Heston model allows for the volatility of the asset price to be stochastic, which makes it more realistic than models that assume constant volatility. The model also has several desirable properties, such as the ability to capture the volatility smile observed in options markets, and the ability to generate paths that are consistent with historical data.*

*The Heston model is often used in option pricing to generate implied volatility surfaces, which are used to price options with varying strike prices and maturities. It is also used in risk management and portfolio optimization to model the behavior of asset prices and their associated risks.*

* **GBM**
* **Vasicek / HW / CIR / Ho Lee / Nelson Siegel**

*The Vasicek, Hull-White, and Cox-Ingersoll-Ross (CIR) models are three popular stochastic interest rate models that are commonly used in finance. Here is a brief description of each model along with some of their pros and cons:*

***Vasicek Model:***

*The Vasicek model is a one-factor model that assumes that interest rates are mean-reverting, with a long-run average and a constant volatility. The model is described by the following stochastic differential equation:*

*drt = α(θ − rt)dt + σdWt*

*where rt is the short-term interest rate at time t, α is the rate at which the interest rate reverts to its long-run mean, θ is the long-run mean interest rate, σ is the volatility of the interest rate, and Wt is a Wiener process.*

***Pros:***

* *Simple and easy to implement*
* *Closed-form solution for bond prices*
* *Can be used to price bonds, bond options, and interest rate derivatives*

***Cons:***

* *Assumes that the interest rate process is Gaussian, which may not be realistic*
* *Cannot capture term structure dynamics, such as the upward sloping yield curve*

***Hull-White Model:***

*The Hull-White model is a two-factor model that extends the Vasicek model by adding an additional factor that captures the dynamics of the term structure of interest rates. The model is described by the following stochastic differential equation:*

*drt = (θ(t) − αrt)dt + σdW1t + λdW2t*

*where θ(t) is the instantaneous mean of the interest rate process, α and σ are as in the Vasicek model, λ is the volatility of the term structure factor, and W1t and W2t are independent Wiener processes.*

***Pros:***

* *Can capture the term structure dynamics of interest rates*
* *Can be used to price a wider range of interest rate derivatives*

***Cons:***

* *Requires numerical methods for bond pricing*
* *May require additional calibration and estimation compared to the Vasicek model*

***CIR Model:***

*The CIR model is a one-factor model that assumes that the short-term interest rate is mean-reverting and follows a square-root process. The model is described by the following stochastic differential equation:*

*drt = α(θ − rt)dt + σsqrt(rt)dWt*

*where α, θ, and σ are as in the Vasicek model, and Wt is a Wiener process.*

***Pros:***

* *Can capture the mean-reverting behavior of interest rates*
* *Allows for negative interest rates*

***Cons:***

* *Assumes that the interest rate process is non-negative, which may not be realistic in some situations*
* *May require additional calibration and estimation compared to the Vasicek model*

*In summary, each of these models has its own strengths and weaknesses, and the choice of model will depend on the specific needs and circumstances of the user. The Vasicek model is the simplest and easiest to implement, but may not capture all the dynamics of interest rates. The Hull-White model and CIR model can capture more complex dynamics, but may require more calibration and estimation.*

**Python:**