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Risk and Intelligence: Exploring the intersection of Finance, Insurance and Artificial Intelligence



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Agenda: Research and Applications

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Nature-Inspired Metaheuristics Fuzzy Logic

02

Machine Learning

Unsupervised and Supervised Learning

03

Neural Networks

Static and Dynamic Artificial Neural Networks



Deep Learning

LSTM architecture, CNN, GRU and Transformer





01 Artificial Intelligence

Nature-Inspired Metaheuristics and Fuzzy Logic



Nature-Inspired Heuristics and calibration

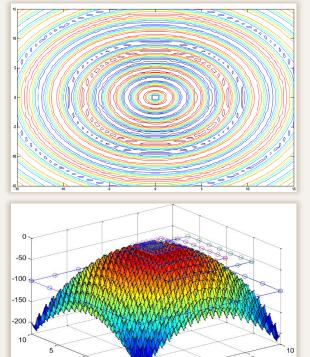
The majority of global search heuristics for finding optimal solutions are inspired by natural processes.

Among the most important **agent-based techniques**:

- Genetic Algorithms (GA),
- Particle Swarm Optimization (PSO)
- Ant Colony Optimization (ACO)

These heuristics can be usefully implemented for the optimal estimation of model parameters, such as GARCH(p,q), lattice models and stochastic dynamics.

A particular nature-inspired deterministic solver is Attraction Force Optimization (AFO).



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Images: Schaffer contour lines and the Rastrigin surface optimized using AFO.

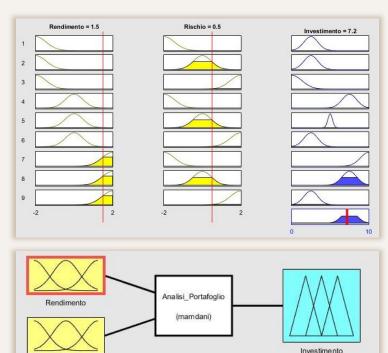
Fuzzy Logic and Risk Aversion

The decision-making process for evaluating the benefit of investing in a financial product follows two sequential phases:

- The first one has a quantitative nature: this step quantifies the expected returns, volatilities and correlations, according to the traditional Markowitz approach

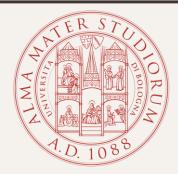
- The second one has a more subjective nature.

Still remaining in a quantitative context, the use of a **soft-computing** technique, such as **Fuzzy Logic**, can be considered as a valid tool for estimating the risk aversion of the investor.



BPER: Images: Fuzzy Logic Designer and the risk aversion modeling using linguistic rules based on Markowitz portfolio framework.

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02 Machine Learning

Unsupervised and Supervised Learning

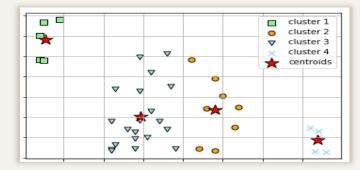


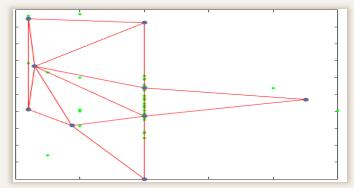
Market Arbitrage Opportunity

Unsupervised Machine Learning algorithms like **Self-Organizing Maps** (SOM), **K-means** and **Fuzzy C-means** can be used for organizing and clustering the information observed on secondary markets, focusing the attention on the recognition of potential anomalies.

Clustering techniques traditionally used for outlier detection can also be coded for finding market opportunities in arbitrage trading.

These methods prove to be effective in Credit Default Swaps (CDS) and fixed income markets.



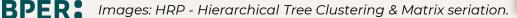


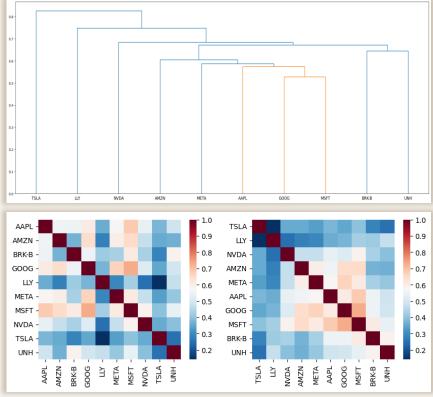
BPER Images: Implementation of K-means and Self-Organizing Maps in Capital Markets for detecting market opportunities.

Optimal Asset Allocation

Hierarchical Risk Parity (HRP) overcomes some of the limitations of Markowitz's model, particularly in managing complex asset correlations, by offering a more refined risk management strategy that ensures balanced risk distribution across the portfolio.

The **Logic Learning Machine** (LLM) method has been implemented together with HRP to enhance the explainability and sensitivity of the weights in an Equity portfolio.





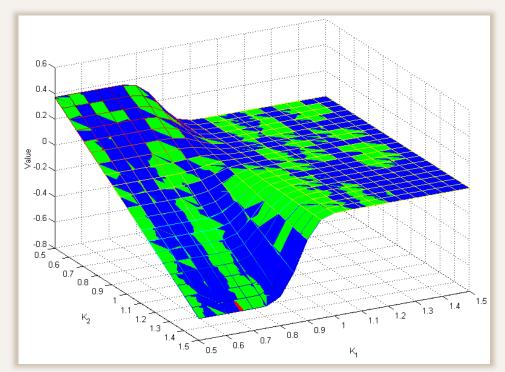
Option pricing: PDE numerical schemes

Partial Differential Equations (PDE) are commonly used for describing the dynamics of an asset.

Initial and Dirichlet's Boundary Conditions allow to specify the payoff features of the derivatives.

If a closed-formula cannot be found, numerical schemes are implemented.

Among those, **Radial Basis Functions** (RBF) are able to reach a very good approximation of the true theoretical option fair value.



BPER Image: Pricing surface of a forex option: comparison between different Radial Basis Functions. Garman – Kohlhagen model.

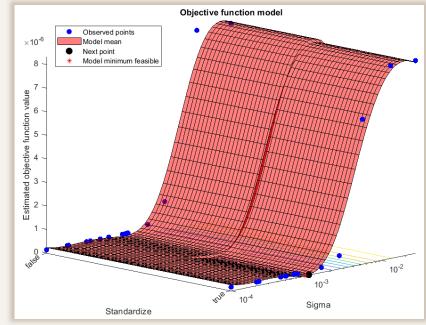
Interest rates term structure models

The Nelson-Siegel, Svensson, and De Rezende-Ferreira models are the most widespread approaches for modeling the term structure of risk-free interest rates.

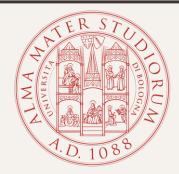
However, they may not perform suitably in turbulent market conditions.

The implementation of **Evolutionary Algorithms** (EA) allows a smarter choice of the initial starting guesses for the nonlinear least squares solver and, consequently, a greater robustness of the model parameter estimations.

As a last resort, **Gaussian Process Regression** (GPR) can be implemented.



BPER: Image: GPR model - Convergence to the minimum observed value of the loss function. Dataset: 5 currencies over 5 years.



O3 Neural Networks

Static and Dynamic Artificial Neural Networks

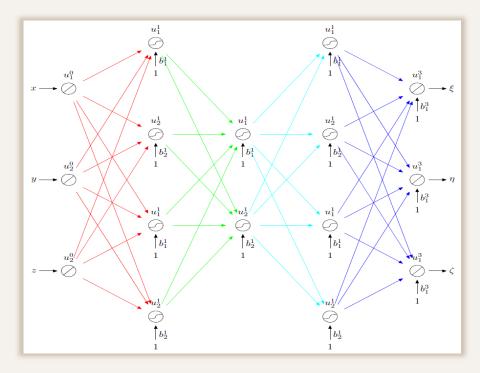


Volatility Surface reconstruction

Data-Missing problems are often circumvented with interpolation in volatility surfaces.

Unfortunately, when a too large portion of the surface is missing, a more complex approach is needed, such as **Auto-associative neural networks**.

The idea is to capture the non-linear relationships of the volatility surface through a **non-linear principal components analysis**, which is incorporated in the net.



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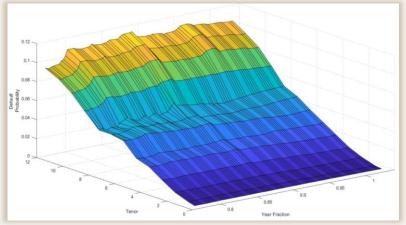
Image: Auto-associative network for nonlinear Principal Component Analysis (PCA). Swaption Volatility Cube reconstruction.

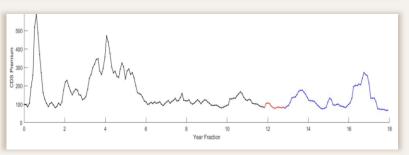
Counterparty Risk estimation

The forecasting aspect in the calculation of the Probability of Default has become more and more important over time as current regulation is increasingly based on a "Through the Cycle" perspective.

To this end, **Recurrent Neural Networks** (RNN) can be applied together with the well-known models able to imply Probability of Default from Market data:

- Hazard rate model (using CDS and bonds)
- the KMV method (Kealhofer, Merton and Vasicek) using equity and balance sheet information



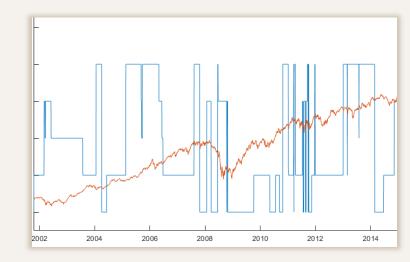


BPER: Images: Forward looking Probability of Default term structure estimation starting from CDS premiums using Recurrent ANN.

Adaptive VaR and CVaR estimation

An algorithmic approach for model selection among different Value at Risk (VaR) and Expected Shortfall (ES) estimation methods can be very useful with the aim of selecting the most prudential estimation of these measures.

In this set of techniques, the diversification of the approaches is important for obtaining more robust results.



Among the models implemented: Historical VaR, Filtered Historical Simulation (FHS), backward looking Monte Carlo VaR and a forward looking MC using **Dynamic Neural Networks**.

BPER. Image: The algorithmic approach for model selection is able to switch to the most prudential model time after time.

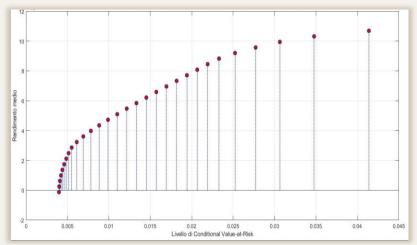
Price Forecasting

Recurrent Artificial Neural Networks can be used for the prediction of returns in a financial time series.

These dynamic artificial neural networks can be divided into two categories:

NAR – Nonlinear Autoregressive network

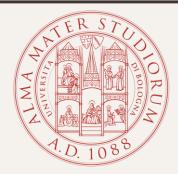
NARX – Nonlinear Autoregressive network with exogenous variables



After a proper check of reaching optimal out-of-sample performances and the absence of error autocorrelation in the model, these forecasting techniques work well. They can be implemented in commodity trading or with traditional models using the predictions as market expectation.

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Image: A forward-looking efficient frontier estimation based on future expected returns computed using a NARX network.



04

Deep Learning

LSTM architecture, CNN, GRU and Transformer



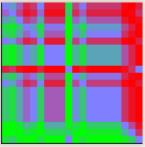
Algotrading and High Frequency Trading

The development of Machine Learning techniques has brought the opportunity to design mechanic trading systems based on Dynamic Artificial Neural Networks.

It has proved very effective to combine traditional technical indicators (such as Exponential Weighted Moving Average – EWMA, Percentage Volume Oscillator – PVO and Stochastic indicator - %K and %D) together with basic Recurrent Neural Networks like NAR or NARX or more complex architectures like **Long Short-Term Memory** (LSTM) or **Gated Recurrent Unit** (GRU).

With a particular reference to High Frequency Trading (HFT), alternative approaches to the traditional autoregressive econometric models have been proposed.

Among them it is worth to quote **Transformers** technology and **Convolutional Neural Networks** (CNN).



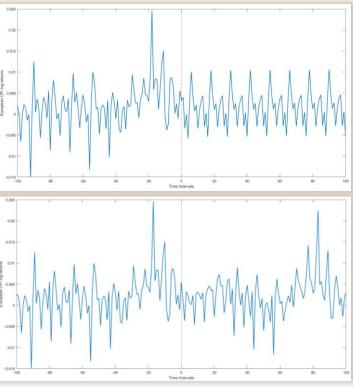
BPER: Image: Graminian Angular Field (GAF) transformation of a time series into an image processed by a CNN architecture.

Seasonality modeling: Inflation indexed Swap

The Standard Market model for pricing Inflation-Indexed Swaps (IIS) proposed by the main info providers in financial markets cannot be considered so reliable from a theoretical econometric perspective.

In fact, the model is based on a 5 years historical normalized seasonality that is repeated over the time till the maturity of the derivative has been reached.

A **LSTM** architecture can help to improve the reliability of the seasonality model as well as the pricing of the IIS.



BPER Images: Historical and perspective estimation for CPI log returns using the market standard approach and LSTM.

Thanks

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AIFIRM – Associazione Italiana Financial Industry Risk Managers

Nature-Inspired Heuristics and calibration

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