

PORTFOLIO DRAWDOWN OPTIMIZATION WITH GENERATIVE MACHINE LEARNING

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InvestSuite

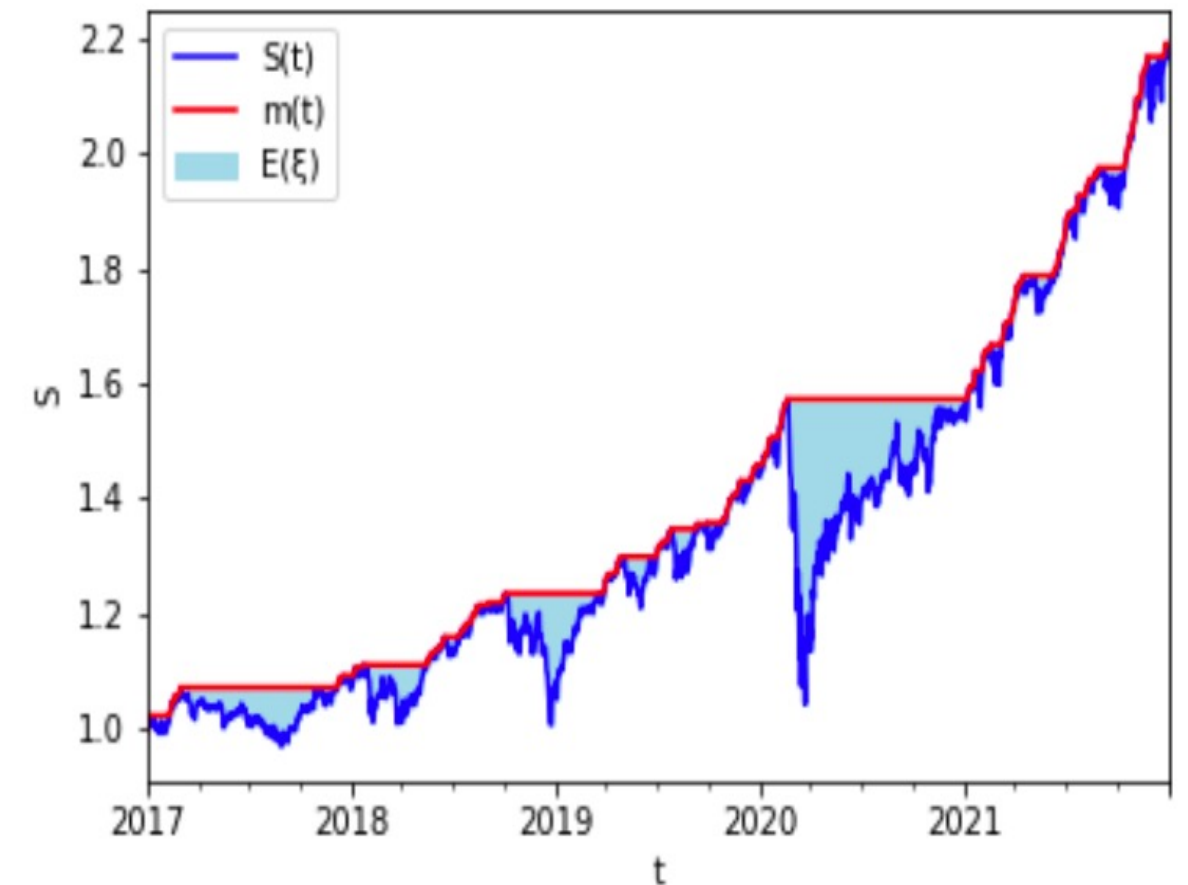


FACULTY OF ECONOMICS AND
BUSINESS ADMINISTRATION

PORTFOLIO DRAWDOWN OPTIMIZATION

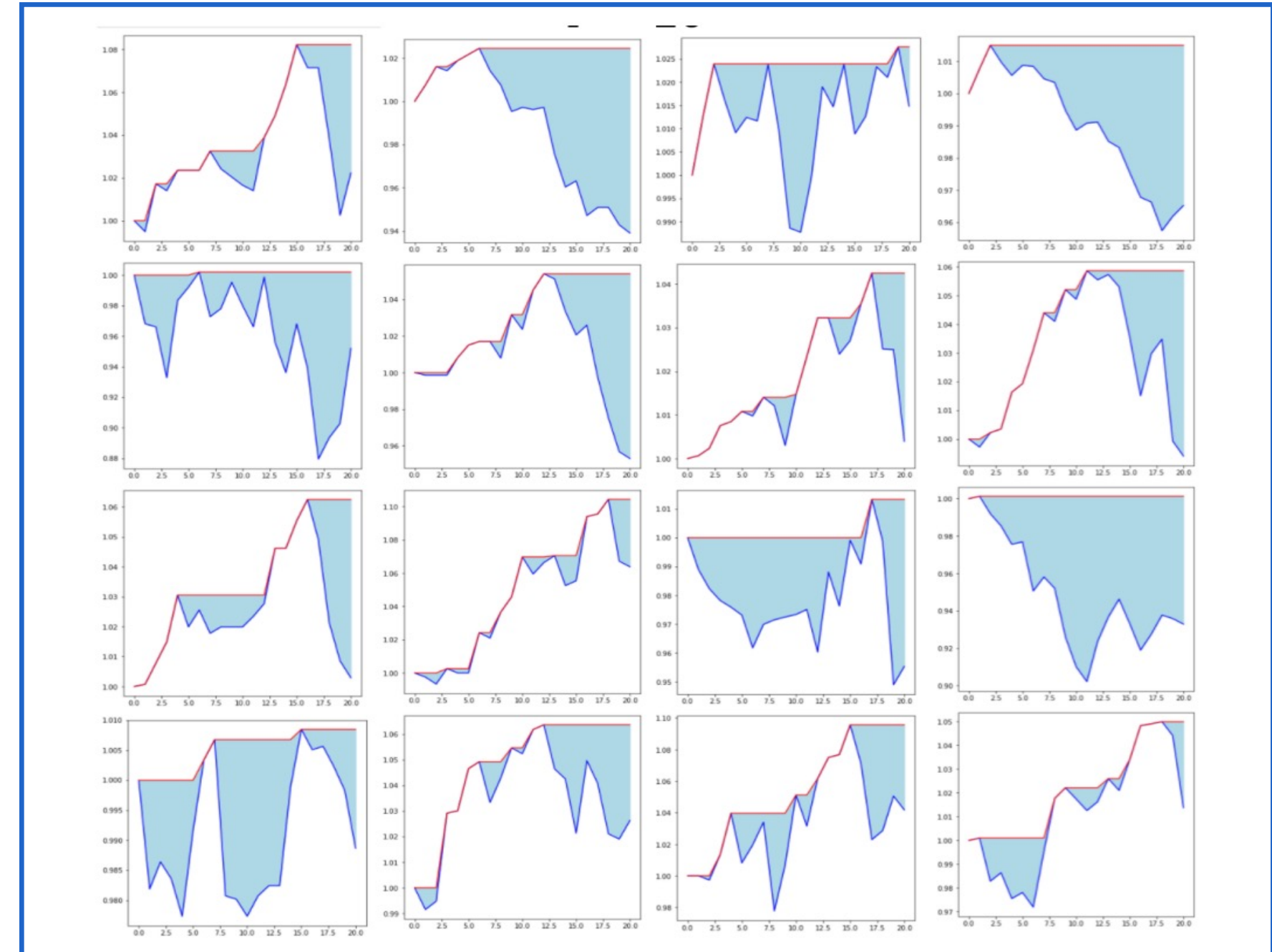
- Minimize *expected* peak-to-valley loss
- Minimize frequency, size and duration of losses
- Dynamic generalization of a deviation measure on the *path space* (Chekhlov et al. 2005)
→ path dependence

$$\begin{aligned} \min_{\mathbf{w}} \quad & \mathbb{E}(\xi(\mathbf{w})) \\ \text{s.t.} \quad & \xi_t = \mathbf{m}_t - \mathbf{w}\mathbf{S}_t \\ & \mathbf{m}_t \geq \mathbf{m}_{t-1} \\ & \mathbf{m}_t \geq \mathbf{w}\mathbf{S}_t \\ & \mathbf{w}\mathbf{I}^N = 1 \\ & \mathbf{w} > 0 \end{aligned}$$



HISTORICAL SIMULATION VS GENERATIVE ML

- Fundamental question: how should we form expectations about the future while looking at the past
- Noise vs. signal
- Unobserved states
- So-called **ergodicity** assumption



MARKET GENERATOR

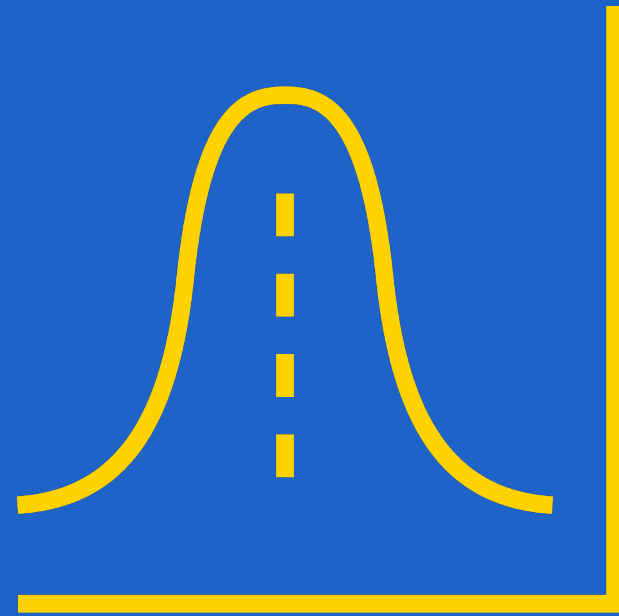
- **Market Generator** =

generative models with the specificity of modelling financial markets

(such as spot asset prices, option prices and volatilities, or order streams in limit order books)

Paper	Year	Architecture	Application
Henry-Labordere [29]	2019	GAN	Option prices
Wiese et al. [30]	2019	GAN	Hedging strategies
Cuchiero et al. [31]	2020	GAN	Volatility models
Ni et al. [32]	2020	GAN	Spot prices
Wiese et al. [33]	2020	GAN	Spot prices
Li et al. [34]	2020	GAN	Order book simulation
Storchan et al. [35]	2020	GAN	Spot prices
Benedetti [36]	2020	GAN	Yield models
Xu et al. [37]	2020	GAN	Spot prices
Pardo and López [38]	2020	GAN	Spot prices
Buehler et al. [39]	2021	GAN	Hedging strategies
Ni et al. [40]	2021	GAN	Spot prices
Pfenninger et al. [41]	2021	GAN	Spot prices
Rosolia and Osterrieder [42]	2021	GAN	Spot prices
Koshiyama et al. [43]	2021	GAN	Spot prices
van Rhijn et al. [44]	2021	GAN	Spot prices
Marti et al. [45]	2021	GAN	Correlation matrices
Coyle et al. [46]	2021	GAN	Spot prices
Wiese et al. [47]	2021	NF	Spot and Option prices
Kondratyev and Schwarz [48]	2019	RBM	Spot prices
Lezmi et al. [49]	2020	RBM / GAN	Spot prices
Wang [50]	2021	RBM / VAE	Spot prices
Buehler et al. [51]	2020	VAE	Spot prices
Fung [52]	2021	VAE	Option prices
Frandsen [53]	2021	VAE	Hedging strategies
Bergeron et al. [54]	2021	VAE	Volatility models
Ning et al. [55]	2021	VAE	Volatility models

Table 1: Overview of the market generator literature



“ SCENARIO-BASED SCIENCE IS MAYBE THE BEST WE CAN DO WHEN DEALING WITH COMPLEX SYSTEMS. ”

DOYNE FARMER

GENERATIVE MACHINE LEARNING

- Approximate data-generating process using flexible (neural) mapping $f_{\theta}(Z)$
- $f_{\theta}(Z)$ transports some source distribution of randomness Z (e.g. Gaussian) into data X' that is statistically indistinguishable from the original sample X , according to some metric \mathcal{L} .
- E.g. in the distributional sense $P(X) \approx P_{\theta}(X')$, according to some distance $\mathcal{L} = \sup_{f \in K} \left| \int f(X) P_{\theta}(X) d(X) - \int f(X) P(X) d(X) \right|$, e.g. Wasserstein distance, total variation (Kullback-Leibler upper bound by Pinsker's inequality), etc.
- Common neural architectures: **GAN**, **VAE**, **RBM**

MACHINE LEARNING ON PATHS

Signature transform :

The collection of all iterated integrals of a path that serves as a **graded summary of a path** describing global and increasingly local properties.

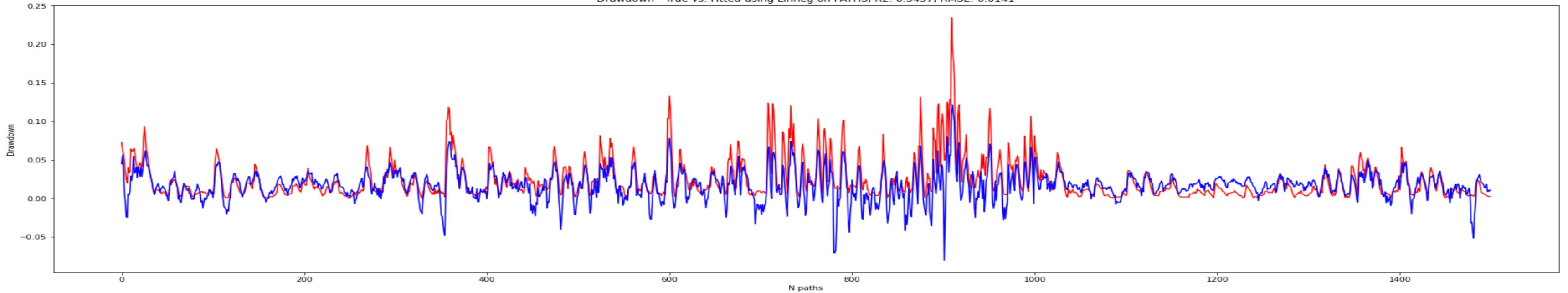
Definition (by Lyons 2014) : $\Phi_M = (1, \Phi^1, \Phi^2, \dots, \Phi^M)$

$$\text{where } \Phi^n = \iiint_{0 < u_1 < \dots < u_k < T} d\gamma_{u_1} \otimes \dots \otimes d\gamma_{u_k} \in (\mathbb{R}^d)^{\otimes n}$$

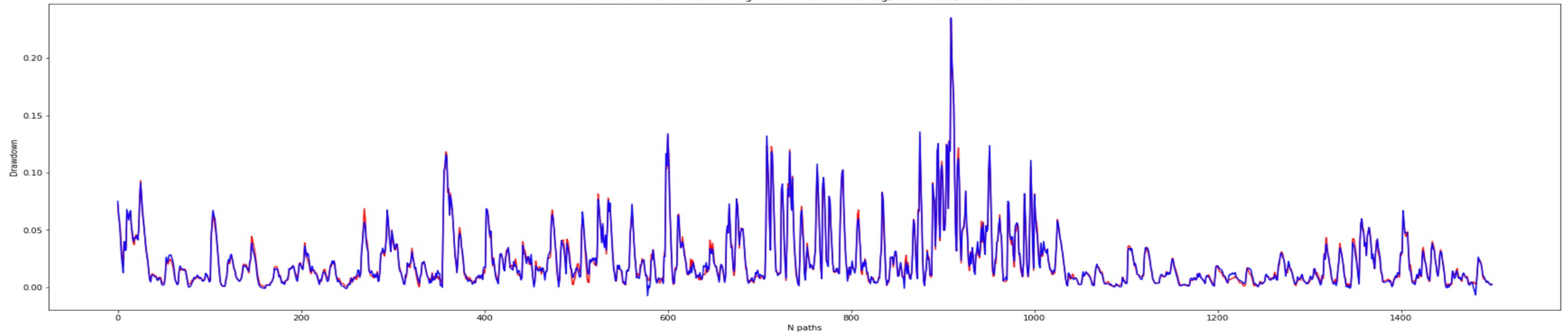
Universality (by Levin and Lyons, 2013) : $\sup_{\gamma \in K} |f(\gamma) - \langle L, \Phi_M(\gamma) \rangle| < \varepsilon$

SIGNATURE UNIVERSALITY AND DRAWDOWN

Drawdown - True vs. Fitted using LinReg on PATHS, R2: 0.5437, RMSE: 0.0141



Drawdown - True vs. Fitted using SIGNATURES and LinReg, R2: 0.9811, RMSE: 0.0029



MACHINE LEARNING ON PATHS: A SIMPLE MARKET GENERATOR

Algorithm 1 VAE market generator given important path feature Ξ

Input Historical price paths $S : [0, T] \rightarrow \mathbb{R}^N$, hyperparameters listed above + signature truncation level M and feature weight α .

Output Trained VAE Market Generator g_θ

- 1: **procedure** TRAIN
 - 2: Divide historical sample into batches \mathcal{B} of length τ , calculate the signatures of these paths truncated at level M , $\Phi_M^{\mathcal{B}}$, calculate the drawdowns Ξ of these paths $\Xi(S^{\mathcal{B}}) = \int_0^\tau (\max_{t_i < t} (S_{t_i}^{\mathcal{B}}) - S^{\mathcal{B}}) dt$ denoted $\hat{\Xi}(S_b)$
 - 3: $\hat{L} \leftarrow \text{LinearRegression}(\hat{\Xi}(S^{\mathcal{B}}), \Phi_M^{\mathcal{B}})$
 - 4: Initialize the parameters θ of the VAE.
 - 5: **for** $i : \{1, \dots, N\}$ **do**:
 - 6: Sample a batch \mathcal{B} and pass it through the encoder g_θ and decoder network g_θ^{-1}
 - 7: Calculate drawdown $\Xi(S')$ of the output sample S' using the differentiable signature approximation: $\langle \hat{L}, \Phi_M(S') \rangle$
 - 8: Define the reconstruction loss term as the weighted average of RMSE error and drawdown loss: $\mathcal{L}_{\mathcal{R}} = \mathbb{E}_{\mathcal{B}} \|S - S'\|^2 + \alpha \mathbb{E}_{\mathcal{B}} \| \langle \hat{L}, \Phi_M(S) \rangle - \langle \hat{L}, \Phi_M(S') \rangle \|^2$
 - 9: $\mathcal{L} = \mathcal{L}_L + \mathcal{L}_R$
 - 10: $\theta \leftarrow \theta - l \frac{d\mathcal{L}(\theta)}{d\theta}$
 - 11:
-

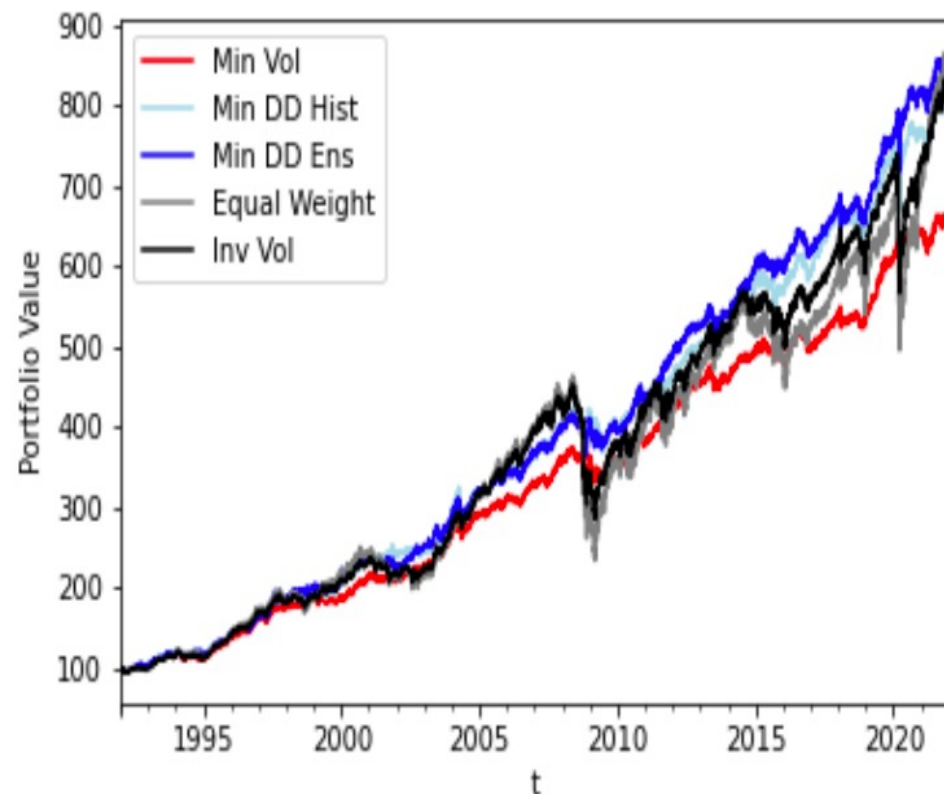
PRELIMINARY RESULTS

- 30y backtest on 4 broad asset class indices: US Equity (S&P 500 index), US Bonds (Treasury index), Real Estate (NAREIT index), and Commodities (GSCI).
- Jan 1992 – Jan 2022, monthly rebalanced
- **Benchmarks:** min vol, inverse vol, equal weight

Value

Summary

Under-water curve



	Return (%)	Vol (%)	ADD (%)	Sharp
Min Vol	6.187	4.822	-2.126	1.283
Min DD Hist	6.967	5.905	-1.911	1.179
Min DD Ens	7.069	5.488	-1.827	1.288
Equal Weight	7.427	10.22	-5.806	0.726
Inv Vol	7.087	7.736	-3.793	0.916



DARE
TO THINK



Emiel Lemahieu
Quantitative Researcher



emiel.lemahieu@investsuite.com



www.linkedin.com/in/emiel-lemahieu