



ভারতীয় প্রযুক্তিবিদ্যা প্রতিষ্ঠান খড়্গাপুর
भारतीय प्रौद्योगिकी संस्थान खड़गपुर
INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR



ICML
International Conference
On Machine Learning

Department of Artificial Intelligence

Learning the ESG Geometry with Domain Aware Language Models

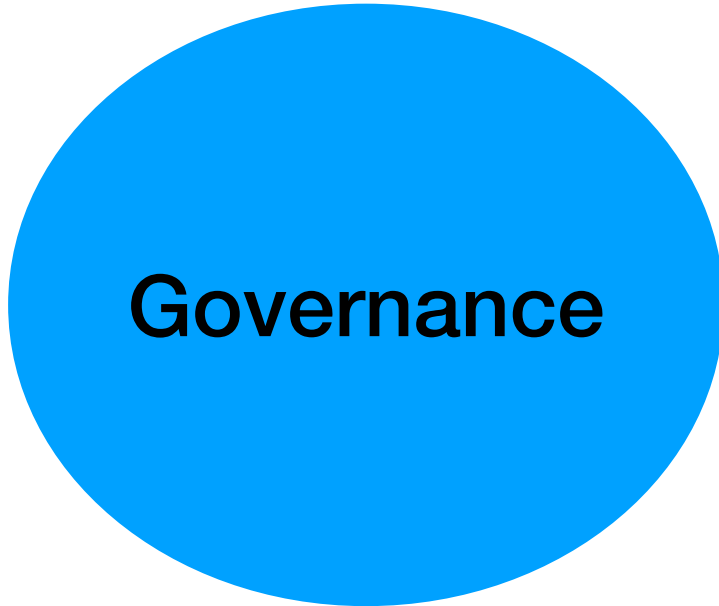
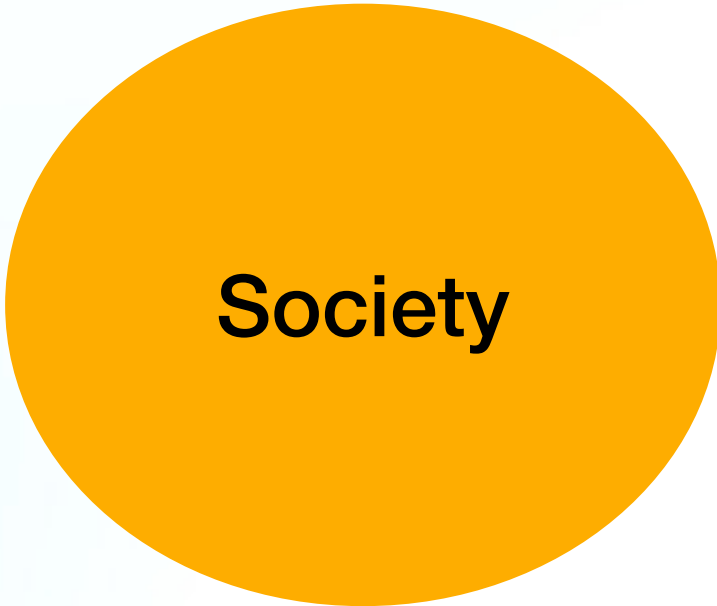
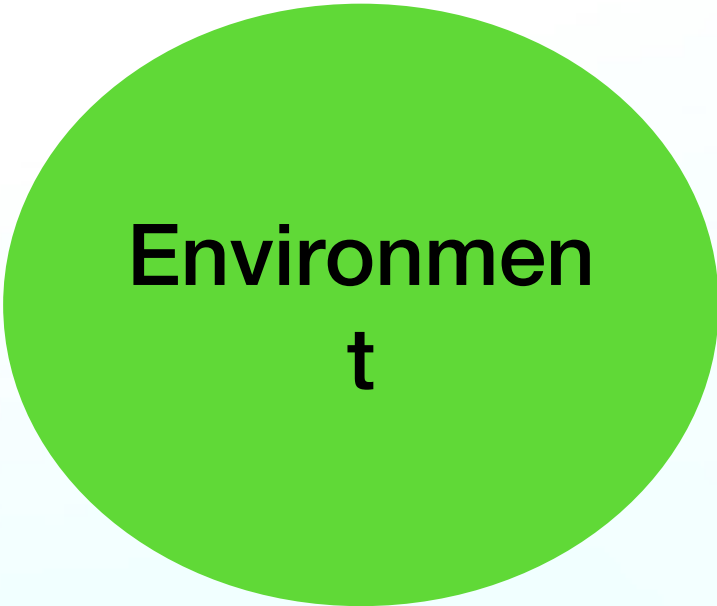
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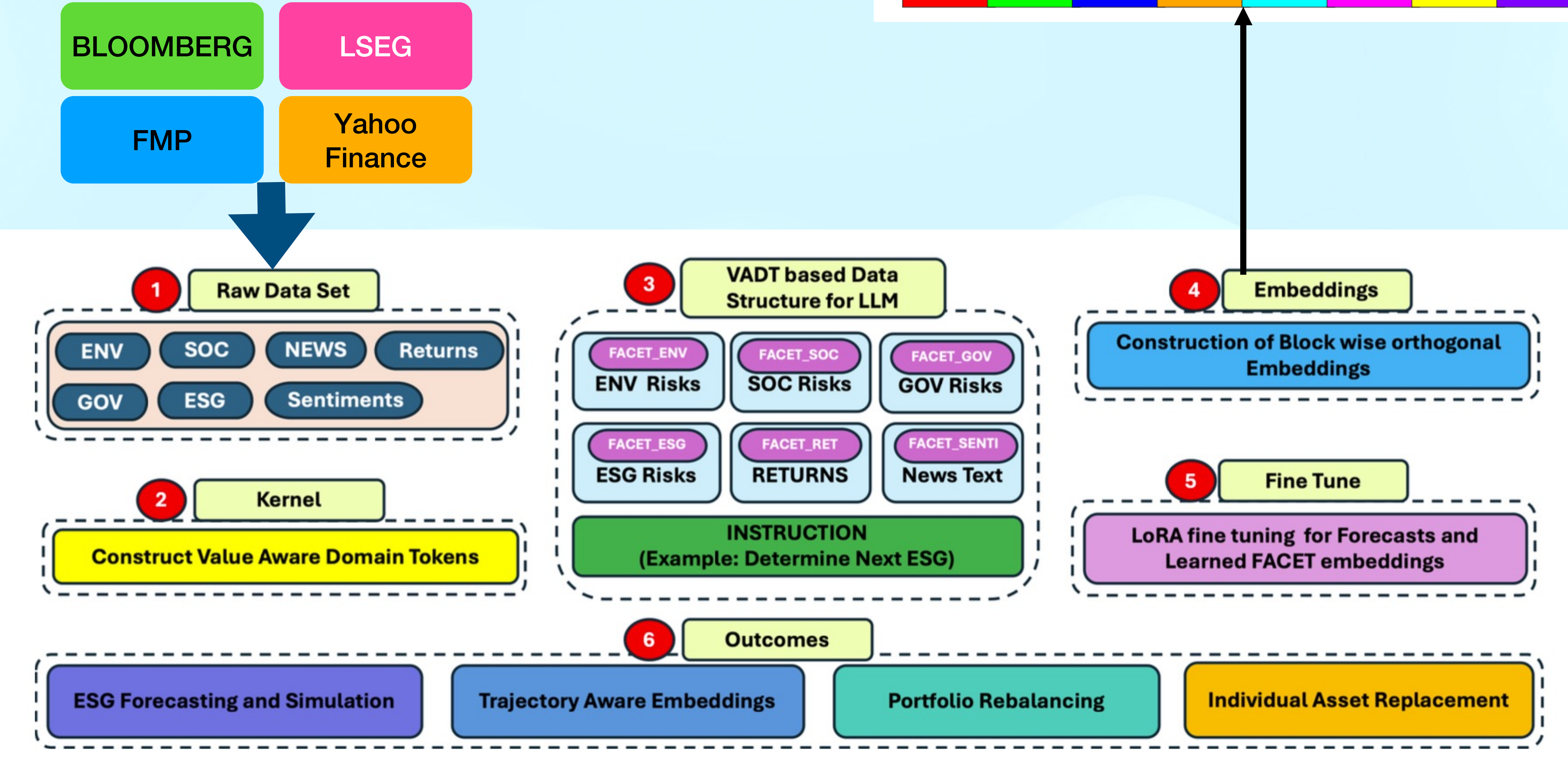
Responsible Investing

- 1. Responsible investing aims to generate positive impact across Environment (E), Society (S), and Governance (G), and rating companies along these dimensions is now widespread, making ESG scores highly popular.
- 2. Allocating retail capital with sustainability in mind could be transformational, yet it remains unclear how individual investors can do so in practice.
- 3. Current ESG solutions cannot model high-dimensional, multi-modal time series capturing the joint evolution of ESG risks, financial returns, news, and sentiment, even though this domain requires jointly reasoning over distinct numerical signals where both numerical proximity and semantic type must be preserved.

Sustainability



Architecture





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Tokenizing Numbers

ESG Ratings for GEN:

14.98	15.01	14.11	14.36
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BPE Tokenizer:

14	.	98	Ġ15	.	01	Ġ14	.	11	Ġ14	.	36
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Block Wise Embeddings

RET 0–95	SOC 96–191	GOV 192–287	ESG 288–383	ESGFO 384–479	ESGSO 480–575	ENV 576–671	SENTI 672–767
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Figure 2. Partitioning of embedding vector into orthogonal spaces.

For a given prefix $p \in \mathcal{S}$, where $\mathcal{S}$ is the set of all token types given as, $\{\text{RET}, \text{SOC}, \text{GOV}, \text{ESG}, \text{ESGFO}, \text{ESGSO}, \text{ENV}, \text{SENTI}\}$, we employ

$$\text{Index of ESG in } \mathcal{S} = 3, \quad |\mathcal{S}| = 8, \quad b = \frac{d}{|\mathcal{S}|}.$$



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5. FORECASTING

RET	SOC	GOV	ESG	ESGFO	ESGSO	ENV	SENTI
0-95	96-191	192-287	288-383	384-479	480-575	576-671	672-767

Partitioning of embedding vector into orthogonal spaces. For a given prefix $p \in S$, where S is the set of all token types given as, $\{RET, SOC, GOV, ESG, ESGFO, ESGSO, ENV, SENTI\}$, we employ Index of ESG in $S = 3$, $|S| = 8$, $b = d |S|$

$$s_i(v) = \sin \left(\pi \left(x_i + \frac{v}{100} \right) \right)$$

where x_i is the normalized block size that assigns each dimension v a unique phase, and $si(v)$ is the sinusoid-coded value of the corresponding numerical value. We also add a quadratic term to $si(v)$ that make embeddings differ as per numerical value.

$$\mathcal{L} = \mathcal{L}_{\text{forecast}} + \beta \cdot \mathcal{L}_{\text{geometry}}$$

where $\mathcal{L}_{\text{forecast}}$ is the standard next-token prediction loss of the LLM, and $\mathcal{L}_{\text{geometry}}$ encourages the model to match distances in the embedding space with Dynamic Time Warp ing (DTW) distances between the corresponding time series, with β controlling their relative importance.

$$\mathcal{L}_{\text{geometry}} = \frac{1}{B} \sum_{b=1}^B w_b \cdot \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N (D_{ij}^{(b)} - D_{ij}^{\text{DTW}})^2$$

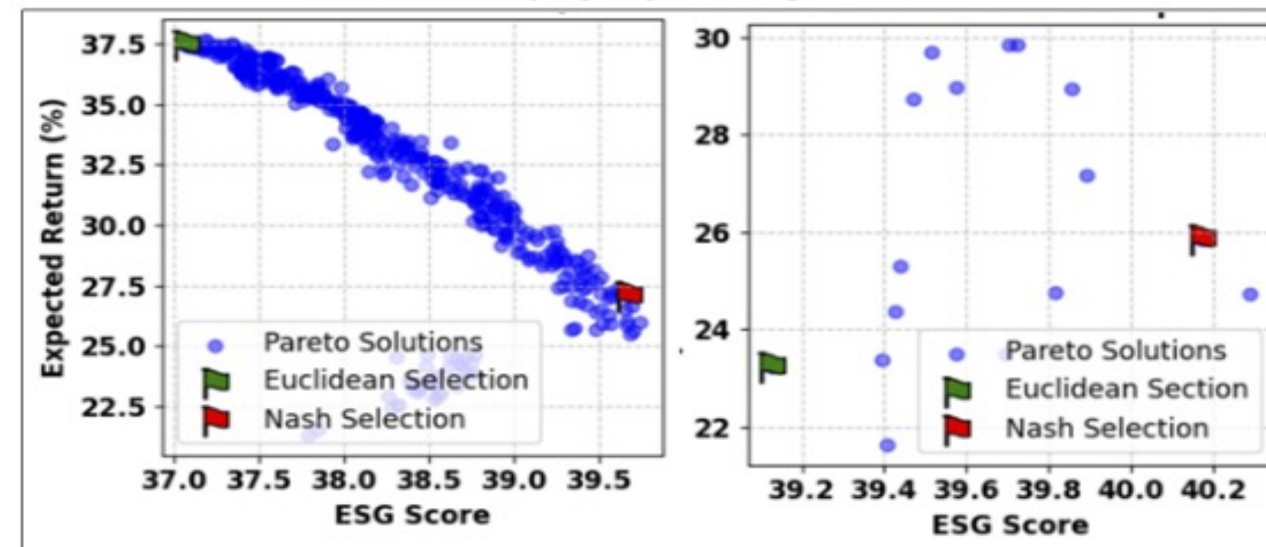
where B is the total number of embedding blocks, w_b is the flag for block b when set to zero will prevent that blocks geometric learning, N is the number of trajectories in the batch, and $D(b) \in \mathbb{R}^{N \times N}$ is the pairwise embedding distance matrix for block b .

6. OPTIMIZATION

Convergence of multi-objective optimization models for ESG-based portfolio rebalancing using the same initial seed portfolio

Metric	NSGA2	NSGA3	SPEA2	RNSGA2	AMOE
Init. Value	\$28,757.28				
ESG Risk ↓	37 – 39.5	39.2 – 40.2	39.25 – 40.75	38.7 – 39.0	38.5 – 40.0
Returns ↑	22.5 – 37.5	22 – 30	24 – 32	21.0 – 21.8	22 – 34
Solutions ↑	471	16	471	471	471
ESG-NASH ↓	39.67	40.17	40.59	39.01	40.23
ESG-EUC ↓	37.1	39.1	39.6	38.66	38.6
RET-NASH ↑	27.0	25.8	32.1	21.67	32.5
RET-EUC ↑	37.46	23.23	31.03	21.81	23.55

Portfolio choices offered by NSGA-II (left) and NSGA III (right) using SAP



$\{ (ENV, \text{ON}, \text{max}), (SOC, \text{ON}, \text{min}), (GOV, \text{OFF}, \text{min}), (ESG, \text{ON}, \text{min}), (\text{Stock Diversity Risk}, \text{ON}, \text{min}), (\text{Liquidity}, \text{OFF}, \text{constraint}), \dots \}$

Minimizing overall portfolio risk

$$f_1(x) = \sum_i w_i ESG_i + \lambda_1 P_{\text{return}} + \lambda_2 P_{\text{div}}$$

where P_{return} is a soft penalty that discourage lowering over all financial return compared to current portfolio and P_{div} discourages allocation of stocks in small quantities. w_i is the portfolio weight of stock i , ESG_i is the ESG risk of asset i , and $\lambda_1, \lambda_2, > 0$ are trade-off parameters controlling the strength of these penalties (full equations for P_{return} and P_{div} are given in supplementary).

Configuration used to assemble the portfolio optimization problem. The modular design allows sustainability objectives to be seamlessly added to financial objectives



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Thank you