Transforming Wall Street: Generative AI Algorithms in Finance

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Wall Street Business Lines

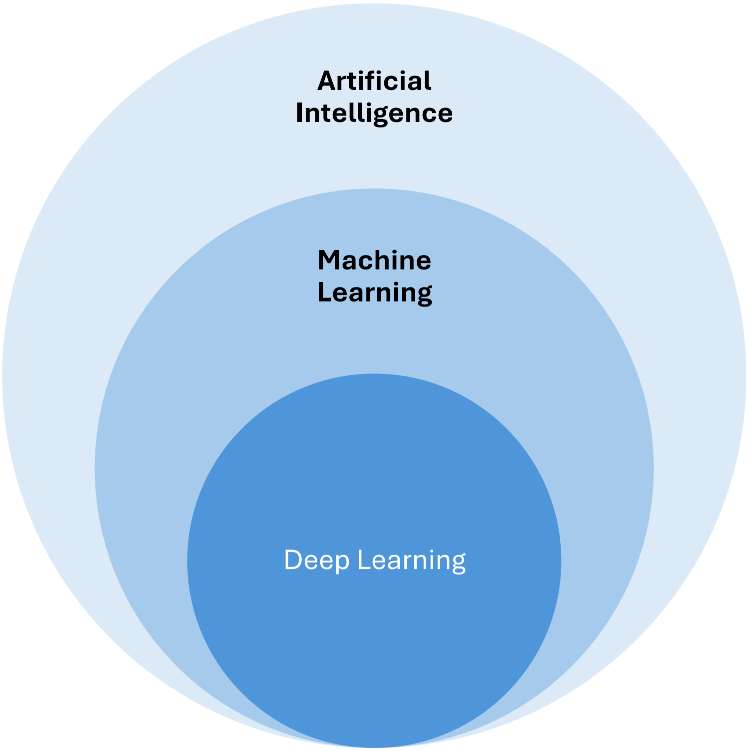
"Sell side" refers to entities who facilitate the sale of financial securities. These entities primarily include investment banks, brokerage firms, and market makers. Their major business lines include underwriting, security research, trading, and advisory services, such as mergers and acquisitions, restructuring, and corporate finance.

"Buy side" refers to entities that primarily engage in purchasing securities and other financial instruments for investment purposes. These entities include mutual funds, hedge funds, pension funds, insurance companies, and asset management firms. Buy-side firms typically manage money on behalf of clients, which include individual investors, institutions, or other funds. The primary focus of buy-side business is to achieve investment goals, which includes capital appreciation, income generation, and risk mitigation.

From 2018 to 2022, Wall Street had stepped onto the journey of adopting machine learning models to support daily business operations. Starting 2023, Generative AI has landed on Wall Street. Experts expect generative AI to transform the way Wall Street firms do business.

Generative AI

Deep Learning Models	Model Input	Model Processing	Model Output
Discriminative	The input data of deep learning models can take various formats (e.g., text, sound, images, videos, etc.) At each timestamp t, data input is processed into a $M \times 1$ vector.	Discriminative models are used to classify or predict. Discriminative Model once trained, can predict labels of the new data points.	The discriminative model can tell you whether a new picture is a dog or a cat.
Generative		Generative models generate new data instances that are like the data it was trained on. Its learning is based on the probability distribution of existing data and predicts new words in a sequence.	The generative model can generate a picture of a dog.



Recurrent Neural Networks (RNN)

The RNN (forward pass)

The **RNN (forward pass)** can be represented by the below set of equations.

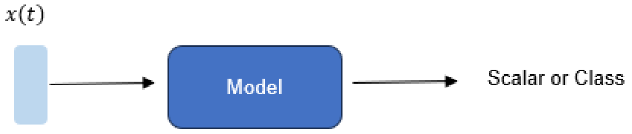
$$a(t) = b + W\, h(t-1) + x(t)$$

$$h(t) = \tanh(a(t))$$

$$o(t) = \mathrm{c} + V h(t)$$

$$\hat{y}(t) = \mathrm{softmax}(\,o(t))$$

Input: At each timestamp t, the input to RNN $x(t)$ is a $M \times 1$ vector.



- **Example 1:** Assume we feed the model with daily data of a stock.

$$x(t) = \begin{bmatrix} open(t) \\ close(t) \\ high(t) \\ low(t) \\ volume(t) \end{bmatrix}, and\ h(t) = \begin{bmatrix} value(t) \\ quality(t) \\ momentum(t) \end{bmatrix}$$

- **Example 2:** Assume we speak a simple language that contains two words alone.

$$x(t) = \begin{cases} \begin{bmatrix} 0 \\ 1 \end{bmatrix}, & if\ x(t)\ is\ \text{"Yes."} \\ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, & if\ x(t)\ is\ \text{"No."} \end{cases} and\ h(t) = \begin{bmatrix} key(t) \\ query(t) \\ meaning(t) \end{bmatrix}$$

Training (parameter estimation): Maximum Likelihood, no closed-form solution, optimization algorithms such as Gradient Descent must be involved.

Linear Regression

$$Y = X\beta + \varepsilon$$

Input: X is a $T \times N$ matrix and Y is a $T \times M$ matrix.

- **Example 1 long panel data (time series)**

Date	Open	Close	High	Low	Adj_Close	Volume	Feature1	Feature2	Feature3	Target (Y)
10/5/2022	144.070007324	147.380004	143.009994506	146.399993896	145.3451232910	79471000	0.3745401	0.0314292	0.6420316	0
10/6/2022	145.809997558	147.539993	145.220001220	145.429992675	144.3821105957	68402200	0.9507143	0.6364104	0.08414	1
10/7/2022	142.539993286	143.100006	139.449996948	140.089996337	139.0806121826	85925600	0.7319939	0.314356	0.1616287	1
10/10/2022	140.419998168	141.889999	138.570007324	140.419998168	139.4082336425	74899000	0.5986585	0.5085707	0.8985542	1
10/11/2022	139.899993896	141.350006	138.220001220	138.979995727	137.9785919189	77033700	0.1560186	0.9075665	0.6064291	0
10/12/2022	139.130004882	140.360000	138.160003662	138.339996337	137.3432159423	70433700	0.1559945	0.2492922	0.0091971	0
10/13/2022	134.990005493	143.589996	134.369995117	142.990005493	141.9597320556	113224000	0.0580836	0.4103829	0.1014715	0
10/14/2022	144.309997558	144.520004	138.190002441	138.380004882	137.3829193115	88598000	0.8661761	0.7555511	0.6635018	1
10/17/2022	141.070007324	142.899993	140.270004272	142.410003662	141.3838958740	85250900	0.601115	0.2287982	0.0050616	1

- **Example 2 cross-sectional data**

Company_Name	Stock_Symbol	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Feature_8	Target (Y)
Apple Inc	AAPL	0.966788871	1.313096369	-0.580041833	-0.175530796	1.16654951	-0.39829316	-1.232156834	-1.4925142	1
Microsoft Corp	MSFT	0.896279168	-0.85057424	-0.306566696	0.475964613	-0.4026403	-1.51025674	-1.658576648	-0.674182	0
Amazon.com Inc	AMZN	-1.046279866	-0.08113937	0.477943563	-0.223885572	-0.3008184	1.1703731	1.667998463	1.1555153	1
Service Now Inc	NOW	-0.543337531	2.236869742	-0.006572633	-0.820159292	1.47940027	1.86527154	1.435186613	-0.1818436	1
Broadcom Inc	AVGO	-0.158840061	1.778067639	-0.127589173	-0.586968204	1.23927101	1.165564129	0.700222405	-0.4388426	0
Meta Platforms Inc	META	-0.50622865	-1.83857528	0.432392853	0.447413679	-1.4368964	-0.42654351	0.357812434	1.17641119	1
Tesla Inc	TSLA	-0.579587034	-2.55930531	0.545837821	0.65256412	-1.9711647	-0.73902424	0.296240973	1.50275298	1
Alphabet Inc	GOOGL	-0.345417712	-1.2564045	0.295247053	0.305866699	-0.9817942	-0.29208281	0.243678818	0.80335182	1
Alphabet Inc	GOOG	0.165604601	0.101186692	-0.085524646	0.008150525	0.11101685	-0.13650025	-0.241953472	-0.2132044	1
Costco Wholesale Cor	COST	-0.333441404	0.274889446	0.118696262	-0.164239745	0.11997486	0.538933306	0.606664614	0.26506984	1

Training (parameter estimation): analytical solution, matrix multiplication, no optimization is involved.

$$\hat{\beta} = (X'X)^{-1}X'Y$$

where

$$(X'X)^{-1}: N \times N$$

$$(X'X)^{-1}X': N \times T$$

$$\hat{\beta}: M \times 1$$