AI: Strategy + Marketing (MGT 853)

AI in Retail + Fashion (Session 9)

Vineet Kumar

Yale School of Management

Spring 2025

Course Logistics

1. Guest Speaker – Please sign up for lunch (need accurate count)

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4. All assignments are now complete

Building Data Science Products at the New York Times

Pablo Romano

Machine Learning Scientist
Ads Data Science

Date: Wed, April 30, 2025
Time: 11:45 am - 12:45 pm
Location: 4200 Qian and Yu Classroom
Evans Hall, 165 Whitney Ave

Pablo Romano is a Lead Machine Learning Scientist within the Advertising Mission at the New York Times. He supports the research, development, and integration of NLP systems and LLMs across several Advertising data products. He has been actively involved in the emerging application of Generative AI to enhance products across the Ads business.

He holds a PhD in Physical Chemistry from the University of Oregon where he developed novel ML methods to study large scale molecular simulations of DNA.

His presentation will cover how ML and AI products are scoped and developed at the New York Times, as well as cover some case studies for our most successful data products.

The New York Times
NEW YORK TIMES ADVERTISING • 2025 SLATE

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8. How can we operationalize the human to AI interface?

How many Units of Items per Store per Year?

AI model with Store manager input

In class Exercise

Small Group Discussion

Forms groups of 3 or so, and explore the following questions.

- How would you design an AI model that would include store manager input?

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- How would you think about incentives for the manager to share this information?

Miroglio – What Happened

- After much internal debate, Francesco Cavarero and Davide Garelli decided to partner with Evo Pricing (Evo) to build an artificial intelligence (AI) system for demand forecasting and inventory replenishment for Miroglio's Elena Mirò brand.

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- Evo CEO Fabrizio Fantini and his team of data scientists worked in close collaboration with Garelli's team and with Miroglio's Chief Data Officer, to come up with the following system.

Miroglio – Designing AI system - A

Initial Inventory Allocation Decisions:

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3. Third decision of allocating specific items to a store was done by first identifying features of each item (e.g., its fabric, category, color, price point etc.). Item matched to previous items with similar features sold in store.

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5. Expensive black blouse was more likely to be allocated to stores that sold many black items (not just blouses), had higher sales of blouses (of all colors), and sold more expensive items

Miroglio – Designing AI system - B

Inventory Replenishment Decisions:

1. Fantini and his team knew that individual Miroglio stores sold few units in each size of SKU $\Longrightarrow$ data at disaggregated level too sparse to predict accurately

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Inventory Replenishment Decisions:

1. Fantini and his team knew that individual Miroglio stores sold few units in each size of SKU $\Longrightarrow$ data at disaggregated level too sparse to predict accurately
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5. Leveraging Image Data: Analyze images of fashion items to abstract key attributes (these might include not only attributes typically identified by humans, such as shape and design, but also many other unique aspects that might be hard for people to describe). It would then correlate these image attributes with sales.

Miroglio – Designing AI system - C

Black Box or Explainable? Fantini wondered whether to propose that Miroglio management adopt the simple, explainable, but less accurate approach, or the state-of-the-art AI method which provided far better forecasts but could be perceived as a "black box." Implementing a state-of-the-art approach could establish Evo as the AI and machine learning pioneer in the fashion industry, but would it create resistance from Miroglio's management?

Miroglio – Designing AI system - D

Including Manager Input on Customers and Local Trends:

1. Idea: providing each store manager with a **non-monetary budget** that they could use to accept or replace replenishment items that Miroglio's HQ proposed.

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2. Garelli explained: "Our Head of Buying has a budget that she uses to decide how many blue jeans or black blouses to buy based on a demand forecast. However, she uses her judgment to modify these quantities from the demand forecast. We can offer a similar budget to store managers and effectively make them the buying heads of their own stores."

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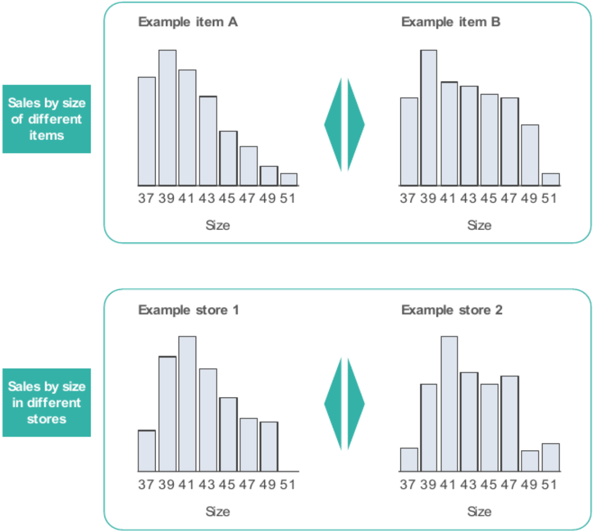
Budget

Budget = store's potential sales in the next four weeks + safety stock of 20% - current stock

Example



Sales by size of different items
Example item A
37 39 41 43 45 47 49 51
Size
Example item B
37 39 41 43 45 47 49 51
Size
Sales by size in different stores
Example store 1
37 39 41 43 45 47 49 51
Size
Example store 2
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Size

Example

	Item 1	Item 2	Item 3
Selling price (€)	100	200	150
Expected sales (units)	5	3	3
Stock (units)	2	4	2

Expected revenues: €1,550 = (5 x 100) + (3 x 200) + (3 x 150)
Potential revenue from stock: €1,300 = (2 x 100) + (4 x 200) + (2 x 150)
Extra coverage: €310 = 20% x 1,550
Budget: €560 = 1,550 + 310 – 1,300

Source: Evo Pricing.

Exhibit 3 Example of Recommended Actions

Store	Item	Stock (units)	Potential (units)	Difference (units)	Action
Store 1	Item 1	10	-1	9	Mandatory release
	Item 2	1	10	-9	Urgent replenishment
Store 2	Item 1	3	1	2	Recommended release
	Item 2	6	5	1	No action
Store 3	Item 1	7	8	-1	No action
	Item 2	2	5	-3	Replenishment

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- Challenge here is that important data may NOT be available to ML system

Takeaways - 2

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Bottomline

AI challenges are embedded in a larger socio-economic context. Need to understand the ecosystem and design everything around the AI system.