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TEACHING NOTE

Miroglio Fashion

Case Synopsis

Late in 2015, Francesco Cavarero, Chief Information Officer of Miroglio Fashion (Miroglio), Italy's third-largest retailer of women's apparel, was trying to bring analytical rigor to the company's forecasting and inventory management decisions. But fashion is inherently hard to predict. Can artificial intelligence (AI) and machine learning replace human intuition in this industry?

"Miroglio Fashion" is a three-part case series that explores the use of data and machine learning in forecasting demand and managing inventory for fashion products. The (A) case introduces the company, describes its retail brands, and explains its existing demand forecasting, inventory allocation, and inventory replenishment practices. The (B) case describes a new model proposed by a consultancy, Evo Pricing (Evo). This case describes how Evo combined human judgment from store managers with machine learning to improve demand forecasting and inventory management. The (C) case describes Miroglio's successful pilot of the Evo plan and the desire by the new CEO, Hans Hoegstedt, to embrace data analytics for additional uses across the company.

Learning Objectives

This case highlights the challenges and opportunities of using data analytics, machine learning and artificial intelligence for improving business performance. It allows the instructors to discuss the following key ideas:

- The challenge of demand forecasting when historical data are sparse and trends change quickly.
- The trade-off between data and managerial intuition for decision-making and how to combine them to get the best of both.
- The decision of "build or buy" analytical skills for a company that is just embarking on the data analytics journey.

This note was prepared by Professor Sunil Gupta with the assistance of Senior Case Researcher David Lane (Case Research & Writing Group) for the sole purpose of aiding classroom instructors in the use of "Miroglio Fashion (A), (B), and (C)," HBS Nos. 519-053, 519-070, and 519-072. Funding for the development of this note was provided by Harvard Business School and not by the company. It provides analysis and questions that are intended to present alternative approaches to deepening students' comprehension of business issues and energizing classroom discussion. HBS cases are developed solely as the basis for class discussion. Cases are not intended to serve as endorsements, sources of primary data, or illustrations of effective or ineffective management. Professor Gupta is a business advisor to Evo Pricing.

- How to encourage adoption of analytical tools by managers who have traditionally relied on their judgment.

At Harvard Business School, the case has been taught in several executive programs (Driving Digital Strategy and CTO Forum) for senior managers. The case can also be taught in MBA, Masters in Data Analytics, and executive courses on technology and operations management, and marketing.

I typically assign the (A) case to students and distribute (B) and (C) cases in class.

Suggested Assignment Questions

1. What are the typical challenges of managing a company in the fashion industry?
2. How critical is demand forecasting and inventory management in this industry?
3. Should Miroglio Fashion invest in artificial intelligence and machine learning?
4. Should the company ignore store managers' input and rely solely on analytical models?
5. Should Miroglio build or buy this analytical capability?
6. How should Cavarero manage internal resistance for this approach?

Discussion Plan

For an 80-minute class session, the case discussion can be divided into the following segments:

• (A) case: The Challenge of Demand Forecasting for Fashion	30 minutes
• (B) case: Designing a Forecasting and Allocation Model	30 minutes
• (C) case: Extending Analytics in the Organization	15 minutes
• Concluding remarks	5 minutes

Case (A): The Challenge of Demand Forecasting for Fashion (30 min)

Q: What are the typical challenges of managing a company in the fashion industry? What makes the fashion industry unique?

I typically start with this broad question so students can appreciate the challenges and difficulties of demand forecasting in the fashion industry before jumping to the conclusion that data analytics is the answer to everything.

Students typically note the following challenges:

- Fashion trends evolve quickly and are hard to predict
- Consumer tastes continue to evolve
- It is unclear if consumers have strong preferences for fashion items or if their preferences are formed by the industry and fashion trend setters
- Fashion items have high margins

- High seasonality in the fashion industry demands speed, and products become obsolete very quickly
- While outsourcing can reduce costs, it reduces the speed to market, which is essential in this industry
- The first few weeks are critical for sales of any fashion item
- The industry relies on price markdowns in the later part of the season to get rid of old inventory
- Traditional firms are facing pressure from industry leaders like Zara as well as ecommerce giants like Amazon. In May 2019, Amazon launched a new service *Drop* that offers fashion items designed by social media celebrities and these items are available for only 30 hours!

Q: How well is Miroglio positioned in this industry? Does it face any unique challenges?

The purpose of this question is to highlight some considerations that are unique to Miroglio. Students typically point out the following:

- Miroglio seems to be caught "in the middle". As the case notes on page 2, its prices are 30% higher than Zara but lower than the Italian "affordable luxury" brands like Max Mara, Pinko, or Twin-set. The lack of clear positioning limits its ability to drive the market and generate consumer demand.
- The company has limited scale and, unlike Zara, does not sell too many units of any single item. As one of the industry experts notes on case page 4, "the number of items of a given style, color, and size sold in each store is small, perhaps only two per week, or perhaps none." This makes demand forecasting even more difficult, if not impossible.
- Not surprisingly the actual sales in a typical store could differ from planned sales by 40% to 50% (case page 4). This shows both the difficulty of demand forecasting and an opportunity to make a significant impact.
- The company owns and operates 1,000 stores. On one hand, this provides an advantage to the company in showcasing its products and having sales people who are dedicated and knowledgeable about its brands. But on the other hand, this increases the firm's fixed cost which can put pressure on its profitability.
- The poor profit position of the company (it has been losing revenues and earnings in recent years as per case page 1) highlights the pressure it is facing.

This discussion shows the tough situation that Miroglio faces and why inventory management is such a critical aspect for the firm.

Q: Given the inherent dynamics of the fashion industry and the limited scale of Miroglio, is it even possible to forecast demand?

Once students understand and appreciate the challenges of the fashion industry, they find it hard to jump to the conclusion that Miroglio should invest in analytics for demand forecasting. Some students suggest that the company should invest in better supply chain management or just-in-time manufacturing taking some cues from Zara. Others suggest that demand forecasting will be difficult, so the company should first invest in optimal pricing and markdown policies instead. The majority of students still believe that it is possible to improve forecasts and reduce the error rates from the current level of 40% to 50%.

To challenge the students who believe that it is possible to build a better demand model, the instructor should highlight the complexity of the task with the following analysis for Elena Mirò, the brand that the CIO wants to use for this exercise:

- In 2015, Miroglio had revenues of about €520 million (case page 1)
- Four major retail brands accounted for 80% of the revenue (case p. 2), or 80%*€520m = €416m
- Elena Mirò had 11% of retail sales (page 2), i.e., 11%*€416m = €45.76m
- Price of its items was €150 to €170 or, on average, €160 (case page 2)
- Therefore, this brand sold €45.76m/€160 = 286,000 units per year
- Elena Mirò had 86 stores in Italy (page 4), so on average each store sold 286K/86 **= 3,326 pieces** per year
- Case page 3 also notes that the full fashion collection at Miroglio averaged around 1,000 SKUs, each of which might come in nine different sizes. Assuming equal number of SKUs across the four major brands, this means there are 250*9 = **2,250 different SKU-size** combinations for Elena Mirò.

In other words, on average, each SKU-size sells 1-2 units per store per year! These calculations show in a very stark fashion the slow-moving nature of Miroglio's items and the difficulty in forecasting demand for its products.[1] This challenge is also noted by D'Antoni on page 3: "At least 30% of our stores receive only one piece of apparel in each size."

This discussion may dampen some of the enthusiasm about analytical modeling, but if students become too skeptical about forecasting (it usually does not happen), the instructor should encourage them to take on the challenge.

Q: What is the role of the store manager? Should we incorporate their input or let the data and algorithms drive the decision for inventory allocation? Do we trust the data or trust the manager more?

Students are split on this question. Arguments in favor of incorporating store managers' input include the following:

- For high-end brands like Elena Mirò, where traffic is slow, store managers get to know their customers well – as suggested by Davide Garelli (p. 4). Store managers have tacit knowledge about consumers' preference, which is very useful when we have sparse data and industry trends change quickly.

[1] An alternative way to highlight this challenge through a rough and approximate calculation is to note that 1,000 SKUs, 9 sizes, and 1,000 stores means that you need 9 million items to supply each store just one item per year of each SKU-size combination. Taking the average retail price of €70 for the three large brands (page 2), this would require annual sales of €630 million, which is greater than the current revenues of €520m. In other words, the company does not sell enough to supply even one item per store each year.

- Data-driven models are correlational in nature and cannot explain causality. We need human input to understand why sales of some items are low or high. Store managers can provide this useful function and their knowledge can help improve the model.

- Getting store managers involved in the decision making will also make it easier for them to trust the model and lower the barriers to adoption of the analytical approach.

- This may also increase the accountability of store managers, otherwise they can blame the model for over or under forecasting demand.

Students who favor data over manager input argue the following:

- Store managers will distort forecasting by bringing their biases into the model.

- D'Antoni believes that store managers do not have the necessary skills to do this task. He highlights how this lack of skill led to increased transportation cost when store managers were allowed to make decisions on inventory reallocation across stores (p. 4).

- Store managers' incentives are not aligned with this responsibility. They should not be allowed to override the model unless their compensation is tied to their decisions.

Q: Should Miroglio build this model on its own or should it "buy" this expertise through an external consultant?

This is the classic build-or-buy decision. Most students recognize that while this may become a core skill for Miroglio in the future, they do not currently have the expertise to build such a model. Therefore, in the short run, it is better for them to outsource it and perhaps over time bring it in-house.

How to select an outside expert is a difficult question that most companies struggle with. Almost every third-party consultancy trumpets its credentials and successes. Many managers hire outside experts either based on the recommendation of their industry peers, or on the basis of prior experience of these consultants in dealing with exactly the same issues with another firm in the same industry.

So, is Evo Pricing the right partner for this task? Although it has experience in the fashion industry, most of its experience is in building analytical models for price markdowns. Evo has no experience in building models for inventory allocation. However, it has worked with Miroglio in the past and its relationship with the company managers may make it easier for internal buy-in.

Q: Will there be internal resistance to analytical models? Who will be most reluctant to adopt this approach? How can the firm overcome this resistance?

The resistance is likely to come from people who will lose the decision-making rights if the firm moves to analytical models. The main person who is likely to point out the deficiencies in the analytical approach will be the Head of Merchandising. So, what should we do about him? Some students suggest that the best approach is to run an experiment to show him the improvement in revenues and profits from the model. However, the internal resistance is usually not only on rational grounds, but also due to loss of power and decision-making rights. Another way to highlight this issue is to ask students the following question: "If the Head of Merchandising is not forecasting demand or allocating inventory, what is he going to do in the future? Should we cut his salary or give him some other responsibilities?"

This is a larger question - as AI and machine learning automate tasks in many industries, senior executives will have to figure out how to gainfully engage their employees by reassigning new tasks and responsibilities to them. In other words, this is not just an analytics problem of designing a forecasting and inventory allocation model, but also a human resource and leadership challenge of assigning new roles and responsibilities to people.

Case (B): Designing a Forecasting and Allocation Model (30 min)

The discussion of the (B) case can be divided into three segments:

- Students group work to design a model ~10 min
- Discussion of students' ideas ~5 min
- Distribute (B) case, let students read it and then discuss the model in the (B) case ~15 min

Student Group Work (~10 min)

A good way to transition to the (B) case is to summarize the discussion so far and the challenge ahead. I typically do this by reminding students that demand forecasting and inventory allocation is inherently difficult in the fashion industry due to fast changing tastes and a large assortment of styles, colors and sizes; it is especially challenging for Miroglio due to its limited scale and slow-moving items.

At this point in time I ask students to form small groups of 2-4 people and come up with a demand forecasting and inventory allocation model for (a) initial allocation of inventory to stores, and (b) inventory replenishment each week during the season. I also tell them that the company values store managers' knowledge and has asked to you to incorporate their input in the model. The goal is for students to come up with a **conceptual** structure of a model (not write a code for it!).

The purpose of this exercise is to help students realize the difficulty in building such a model. It is easy to suggest that the company should adopt analytics, but it is hard to actually construct such a model, even at a conceptual level.

Discussion of Student Ideas (~5 min)

In general, students find this exercise very hard. Many of them tend to fall back on the current system of using historical data and using some sort of regression to forecast sales in the future. But this is problematic since we have sparse data and the current system has a 40% to 50% error rate. And it ignores managerial judgment.

Another option suggested by students is to use demographics and other characteristics of each store location to model demand and allocate inventory. They argue that demand in the heart of Rome will be quite different from a mountain city or a beach town. The current clustering algorithm used by the company ignores these characteristics. This is a reasonable argument and may indeed improve the model accuracy.

Some students also suggest removing the effects of price markdowns from the historical data before forecasting demand. Again, this is a good argument because price markdowns may inflate the inherent demand of certain items or stores. Some students also point out that historical sales data does not capture stockouts and therefore past sales may underestimate the demand of certain items.

To incorporate store managers' input, students invariably fall back on the incentive and compensation argument, i.e., allow store managers to modify the model's forecast and allocation but tie their compensation to the performance of their stores.

Miroglio's Forecasting and Allocation Model (~15 minutes)

Distribute the (B) case and allow students a few minutes to read it, and then discuss the key aspects of the proposed model.

The (B) case describes the two key components of the model – initial inventory allocation at the beginning of the season and weekly inventory replenishment thereafter.

Initial Inventory Allocation

Initial inventory allocation involved three decisions: (a) what percent of inventory to allocate at the start of the season, (b) how many items to send to each store, and (c) which items and sizes to send. The description of how Evo handled these three decisions are described in the (B) case and is straightforward. Perhaps instructors can highlight the third decision which uses a similarity index to handle the sparse data problem. As the example in the case suggests, an expensive black blouse is 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.

Evo did not spend much time improving the store clustering method as suggested by some students, partly because they focused more on improving the inventory replenishment component because they believed that a better replenishment model would require a lower proportion of initial allocation of inventory to stores (similar to the backward induction method of solving a dynamic problem).

Inventory Replenishment

The (B) case describes three steps for weekly replenishment decision – initial forecast, incorporating store managers' input, and optimal allocation of stock. The case clearly describes how Evo built these three models and it may be useful for the instructor to slowly walk the students through them.[2]

A few things to highlight in each step of the model:

Step 1: Initial forecast

Three things to note here:

- First, recognizing that the data for each item, size and store for a category is very sparse, Evo decided to aggregate data at the item-store level for each category (a category could be women's blouse, an item would be a particular SKU of a blouse that captures its style and color).
- Second, to separate the effects of price markdown and seasonality, they first removed the effects of price markdowns to estimate the seasonality coefficient which was later used for future demand forecast.

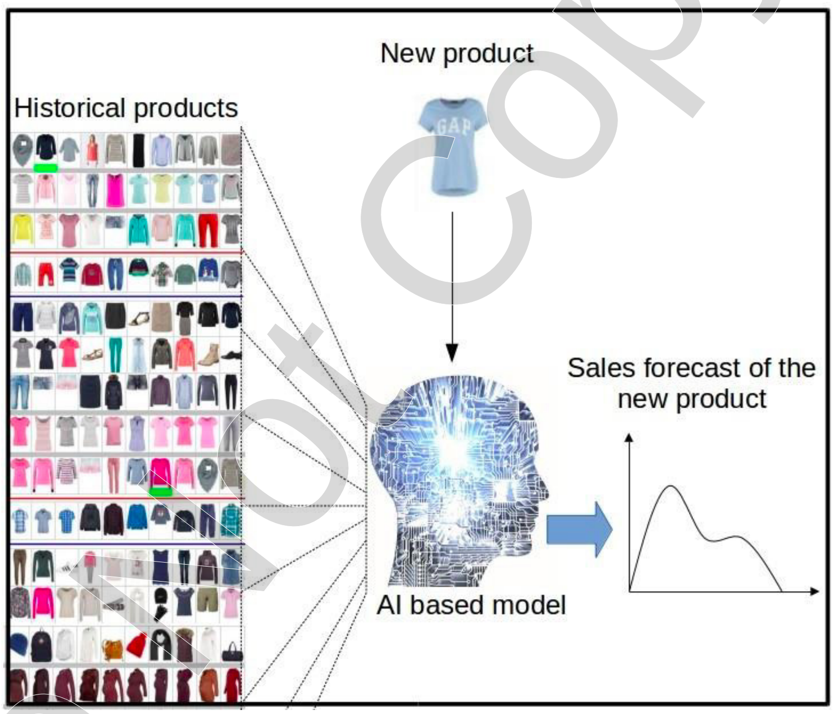
[2] Interested readers may want to see the academic article published by the Evo team that describes the technical details behind this replenishment model: Sirovich, Roberta & Craparotta, Giuseppe & Marocco, Elena. (2018), "An Intelligent Fashion Replenishment System Based on Data Analytics and Expert Judgment," in *Artificial Intelligence for Fashion Industry in the Big Data Era*, Sébastian Thomassey and Xianyi Zeng (eds.), Springer, Singapore, pages 173-195.

- Third, the aggregate demand of an item-store model was then used to estimate the demand for each size as per Exhibit-1 of the (B) case. This exhibit shows that smaller sizes generally do well for item A and store 1.

In addition to this approach, Evo developed an alternative method that used image analysis to generate correlations between historical sales and product features. That is, beyond confirmation that black blouses sell well, Evo examined specific attributes of a given black blouse, such as its buttons, collar, or cut, or features that might be hard for people to describe. Evo's model then looked for correlations between these features and sales of both (1) black blouses with those individual features and (2) sales of other products with one or more of the same individual features, such as other items with a similar collar. This process generates many more data points for processing, thereby improving correlations to sales and thence forecasting accuracy. While the data that comes from this approach improves the model's predictions significantly, neither the model nor its creators can explain why.

This method of finding similarity in images of different items and correlation between their sales can also be used to forecast the sales potential of a completely new item that was never sold before (see **TN Figure A**).[3] Depending on the objective of the class, instructors can also use this opportunity to briefly describe how image analysis works.

TN Figure A Using Image Analysis and AI for New Product Forecast



Source: Evo Pricing, November 2018.

[3] For further reading on the use of AI and image analysis in the fashion industry, please refer to the following articles: [1] Christian Bracher, Sebastian Heinz, Roland Vollgraf (2016), "Fashion DNA: Merging Content and Sales Data for Recommendation and Article Mapping," Machine Learning Meets Fashion workshop, KDD 2016 Conference, San Francisco, USA, March 14; and [2] Halah, R. Stiefelhagen and K. Grauman (2017). Fashion Forward: Forecasting Visual Style in Fashion. 2017 IEEE International Conference on Computer Vision (ICCV), Venice, pp. 388-397.

Q: Should Miroglio adopt the image analysis forecasting system that may be hard to explain but has better forecasting accuracy, or should it stay with a simpler and easily explainable model with less accurate forecast?

Students are divided on this question. Some argue that Evo has more to gain from starting with its simpler model and by introducing the more complex image analysis only after Miroglio managers at both headquarters and in stores observe improved efficiency and sales gains from the simple model. Others argue that such patience is unnecessary, and that store managers have no need to know that the image analysis is being used in conjunction with historical sales data to allocate current inventory. These students believe that store managers will not trust a complex model that they cannot readily understand, but that they will accept the model if it generates results.

In the end, Evo suggested the simpler model as the starting point and only after its successful test results (as described in the (C) case) and implementation, they moved to image analysis after about a year.

Step 2: Incorporating stores managers' input

Evo came up with a clever method to incorporate store managers' input. Instead of giving them complete authority of overriding the model, they created an artificial budget within which the store managers could operate. Effectively the system worked as follows (see case Exhibit 2):

- HQ proposed inventory replenishment of various items based on the model forecast.
- Stores were allowed an additional 20% buffer in expected revenue on top of this forecast.
- Store managers then had a budget = Expected revenue (as per model forecast) + 20% buffer – value of current stock.
- Store managers could change the replenishment request so far as they remained within their budget. In other words, if they wanted to order more of a certain item, they had to reduce the order quantity of another item to remain within their budget.

Too much control in the hands of store managers is likely to lead them to over-order inventory to avoid stockouts. The creation of the artificial budget (described on (B) case p. 2) is a useful constraint on this behavior. Giving up one inventory item in order to receive an additional item that a store manager believes to be more likely to sell gives her a way to adjust the initial allocation, while potentially increasing her acceptance of and engagement with the allocation system.

As a result, the artificial budget is a useful tool to augment store manager capabilities, and Miroglio will benefit to the extent that it can retain engaged store managers as the firm transitions towards a data-driven forecasting and allocation system. There is also valuable information about store manager effectiveness to be gained by comparing sales stemming from headquarters' initial inventory allocation against those following store managers' adjustments.

Evo tested the model with and without store managers' input and found that incorporating managers' input improved overall performance.[4] The company also found an additional benefit of this approach – it provided the central merchandising team a frequent "survey-like" review of consumers' preferences based on the requests of store managers. To capture this information, Evo created a popularity index based on the ratio of demand to supply of a particular SKU. Specifically, for each item i in week w, it defined the popularity index as:

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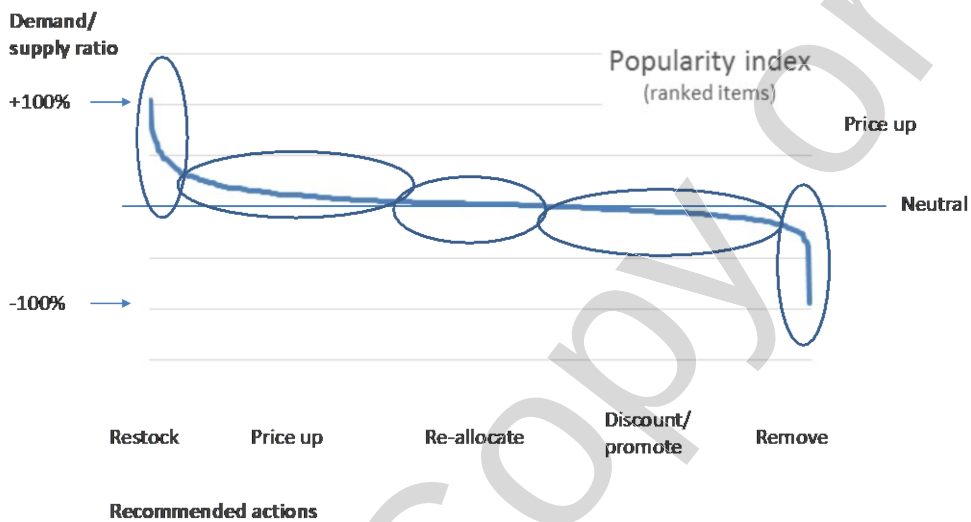
[4] A classic article that discusses combining data and human judgment is by Robert Blattberg and Stephen Hoch (1990), "Database Models and Managerial Intuition: 50% Model + 50% Manager," *Management Science*, August, Vol. 36, No. 8.

$$\emptyset_i^w = min\left(1, \frac{\sum_{s,j} R_{ijs}^w}{\sum_{s,j} E_{ijs}^w}\right)$$

Here the numerator, which captures demand, is the net total request for item *i* across all stores *j* and sizes *s* in week *w*; and the denominator, which captures supply, is the total inventory in the stores in the replenishment program. The popularity index is bounded between [-1,1]. Ranking all the SKUs of the brand at a given week *w*, Evo discovered a S-shaped curve of item popularity (see **TN Figure B**).

TN Figure B Ranked Popularity Index of SKUs



Source: Evo Pricing, November 2018.

Q: Will some managers' input be better than others? Should Miroglio change managers' budget based on their accuracy?

This is a tough question and requires careful monitoring of each store managers' performance when the market conditions are quite volatile. It may be hard to separate luck from skill in such a dynamic market, so even though this idea sounds reasonable in theory, it is hard to implement in practice. It may also put undue pressure on store managers and may shift their focus from selling to forecasting.

Q: As the model learns from store managers' input over time, would we need their input in the future?

It is possible that the model learns over time from store managers' input. Even though the value of store managers' input may decline over time, it could still be valuable if market conditions continue to evolve over time. Allowing some control to store managers may also continue their engagement with the system.

Step 3: Optimizing stock allocation

The last step uses the input of all store managers and optimizes stock allocation to maximize expected firm profit by considering the available stock of items in the warehouse, their demand from stores, the transportation cost, and the margin of the items.

Case (C): Extending Analytics in the Organization (15 min)

After a thorough discussion of the (B) case, distribute the (C) case and give students few minutes to review its content. If the instructor is short on time, s/he can describe the main points of the (C) case to start the discussion. The (C) case states that Evo conducted A/B testing of its simpler model in Elena Mirò stores (p. 1). The pilot program elicited substantial store manager participation and showed it generated significant increase in both revenues and margins.

The extension of the pilot to Miroglio's other retail brands did not include store managers' input. Was it a mistake?

Q: Should Miroglio have included store managers' input for the other three brands as well?

Store managers' input was very valuable for Elena Mirò, so why not include it for the other three brands? Was it wise for Miroglio to ignore this useful input in the model for the remaining three brands? Some students agree with Miroglio's decision while others are more skeptical. Most suggest that the company should test the two approaches to see which one works best, in other words let the data speak for itself.

However, this raises a more general question – when is human judgment a good complement for a data-driven model? One way to highlight this issue is use **TN Figure C** with a continuum showing fast-moving items such as grocery products at one extreme and slow-moving products such as Elena Mirò apparel at the other. Miroglio's three fast-fashion apparel brands fall somewhere in between the two extremes.

TN Figure C AI and Human Judgment

Source: Casewriter.

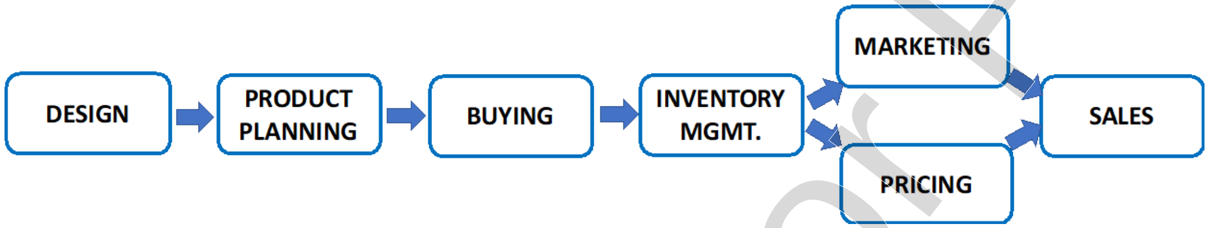
Using this figure, the instructor can ask students if managerial judgment should be included in the demand forecast of grocery products. Most students are quick to point out that machine learning models without human judgment will be quite accurate for groceries since we have enough historical data for frequently purchased items. In addition, market conditions in grocery products are fairly stable so historical data are good predictors of future demand. In fact, including human judgment might bring in biases and might deteriorate the accuracy of machine learning models when there is sufficient data. Miroglio's three other brands (Motivi, Oltre, and Fiorella Rubino) move faster than Elena Mirò items, but nowhere close to the grocery products.

In fact, Fabrizio Fantini, the CEO of Evo, told me that they tested the model with and without store managers' input for Miroglio's three remaining brands as well and the model with store managers' input performed better. However, Miroglio's management still decided to exclude store managers' input for the fear of over burdening them with more responsibility.

Q: In October 2016, Hans Hoegstedt joined as the new CEO. How should Hans extend the analytical capabilities within the organization?

There are two directions that students can go with this question: extend analytics beyond inventory management; and bring the analytics capability in-house. To discuss the first issue, instructors may want to use **TN Figure D** and some of the ideas suggested by Hoegstedt on (C) case p.2.

TN Figure D Various Operations of Miroglio Fashion



Source: Casewriter.

After successfully managing inventory allocation, Miroglio can move both upstream and downstream across its various operations.

On the downstream side, marketing and pricing are crucial decisions for driving sales. Dynamic pricing is a complex area that requires price markdowns over time. Pricing decisions become more complex if the firm wants to consider the complementarity and substitutability of various items. In other words, price discount for item A may increase the sales of not only item A, but also its complement item B, and it may hurt the sales of a substitute item C – all of which may have different margins and different stock levels at a point in time.

Marketing decisions, such as which items to promote in the store or the website, also have a substantial influence on sales. And marketing and pricing decisions are correlated – in other words, if an item is promoted heavily in the store or gets significant exposure on the website, it may not need a significant price discount compared to another item that has limited awareness. On the flip side, it is also possible that there is a strong positive interaction between marketing and price, so it might make sense to promote and discount an item at the same time. Capturing these interactions between decisions and between complement/substitute items over time is a nontrivial modeling exercise.

On the upstream side, buying and product planning decisions can be improved so that the right amount of the right assortment is ordered in the first place. Popularity index generated from the model in the (B) case can be useful input for these decisions for the next season's planning cycle. Data can also be used to decide the ideal location of stores.

Finally, analytical models and image analysis can also be used to predict fashion trends to help designers. Can data analysis replace creative designers? This question generates lot of debate among students and is the subject of hot debate in the industry as well. In recent years, Art Peck, the CEO of Gap, replaced many creative directors in the company in favor of data analytics. StitchFix, an innovative fashion startup also heavily uses data analytics (along with fashion consultants) to create new personalized items for its subscribers. Amazon has been developing an AI fashion designer.[5]

The second issue of whether to bring the analytical capabilities in-house or not depends on a few considerations. First, does the CEO believe that this is a core skill for the success of the company?

[5] Will Knight, "Amazon has developed an AI fashion designer," *Technology Review*, August 24, 2017, https://www.technologyreview.com/s/608668/amazon-has-developed-an-ai-fashion-designer/ accessed June 27, 2019.

Second, can Miroglio acquire the necessary talent to do this well? Third, given the rapidly evolving nature of this technology, can Miroglio keep up with the advances in AI and machine learning? Fourth, do the economics justify bringing these skills in-house? Finally, is it the right time and right priority for the company?

TN Exhibit 1 presents a suggested board plan for the class discussion.

Concluding Remarks (5 min)

To conclude the class, instructors can highlight the following:

- key aspects of building an analytical model (e.g., removing markdown effects from data before forecasting, aggregating data when it is sparse, using image analysis etc.)
- when and how to combine data and managerial intuition
- how to get buy-in within an organization (by incorporating managerial input in the model and by giving manager some control within bounds; by assigning them new roles and responsibilities; and by showing the improvement through A/B testing)
- the scope of analytics in an organization (e.g., Miroglio can go leverage data analytics across the entire value chain including design, merchandising, buying, inventory management, marketing, and pricing)

Depending on the interest of the instructor and the position of the case in the class, it may also be suitable to do a short lecture on various machine learning models (e.g., supervised and unsupervised learning models).

TN Exhibit 1 Suggested Board Plan

Challenges

Fashion Industry

- Trends and taste evolve quickly
- High seasonality
- First few weeks critical
- Price markdowns
- Pressure from ecommerce
- …

Miroglio

- Caught in the middle
- Slow moving items
- 40%-50% error in forecasting
- Revenue and earnings down
- …

Assortment Complexity

Miroglio Revenue = € 520m
Retail brand share = 80% of revenue
Elena Mirò share = 11% of retail brands
Elena Mirò Rev. = (80%) x (11%) (€ 520) = € 45.76m
Average price = € 160
No. of Elena Mirò stores = 86
Annual sales per store = 45.76/(160x86) = 3,326
Assortment = 250 SKU x 9 sizes = 2,250

Store Management Input

Yes

- Tacit knowledge
- Engagement
- …

No

- Bias
- No accountability
- …

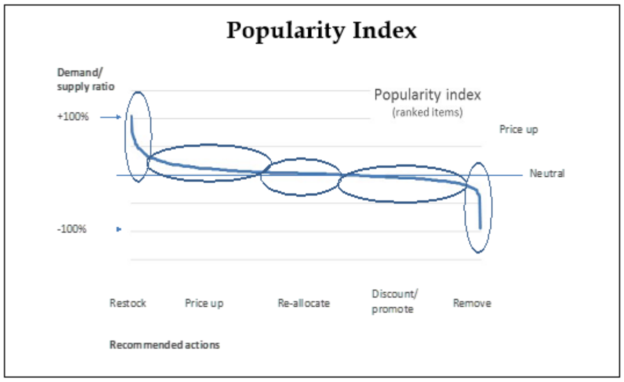
Building an Analytical Model

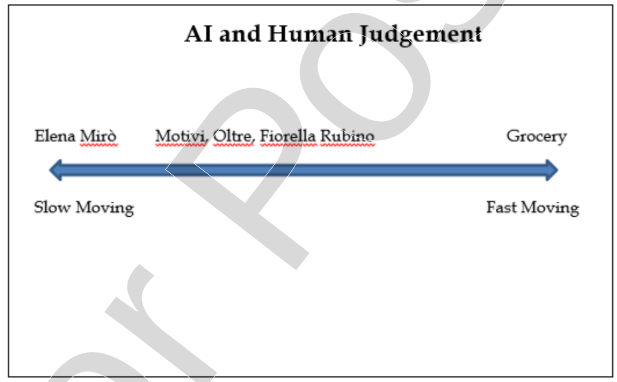
Initial Inventory

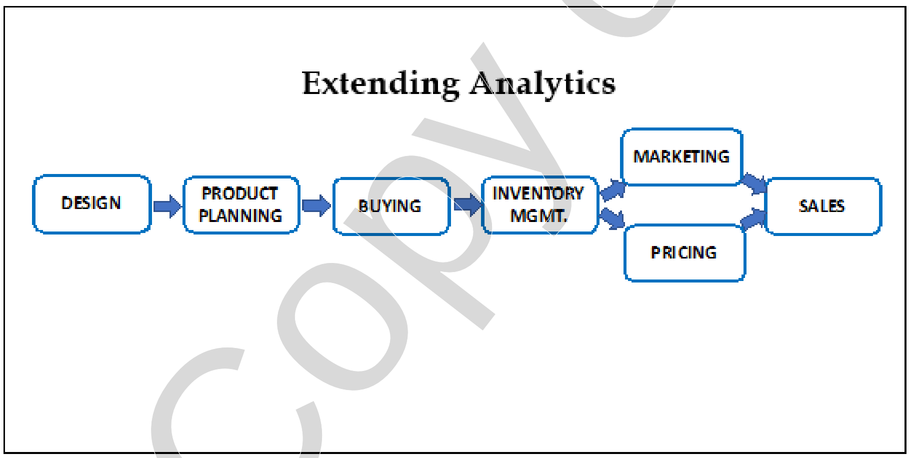
- % inventory to allocate
- How many items/store
- Which items/size

Inventory Replenishment

- Initial forecast
- Including managers' input
- Optimizing across stores


Popularity Index
Demand/
supply ratio
+100%
-100%
Popularity index
(ranked items)
Price up
Neutral
Restock
Price up
Re-allocate
Discount/
promote
Remove
Recommended actions


AI and Human Judgement
Elena Mirò
Motivi, Oltre, Fiorella Rubino
Grocery
Slow Moving
Fast Moving


Extending Analytics
DESIGN
PRODUCT PLANNING
BUYING
INVENTORY MGMT.
MARKETING
PRICING
SALES