crunch

ADVANCED ANALYTICS & AI

A 2020 CLIENT STORY

# GETTING END-OF-SEASON DISCOUNTS RIGHT.

*How Schoenen Torfs Embraced Advanced Analytics for Markdown Pricing and Achieved Staggering Results*

Here is how Crunch Analytics demonstrated the impact of replacing a rule-of-thumb pricing process by an analytics-driven markdown process.

One that is enabled by automated data retrieval, pricing algorithms, and a set of easy-to-use dashboards indicating actions or showing results. One that lead to a double-digit increase in sales season revenue.

# IN SHORT

*Situation, Solution & Success*

### Situation

Schoenen Torfs is a well-established player in the Belgian retail industry and perceived as a frontrunner by many. As such, Torfs is always looking for innovations that help to maintain its position at the forefront of the pack.

Deciding on end-of-season discounts (markdown pricing) was performed using a traditional process, that proved ample opportunity for improvement using advanced analytics.

### Solution

The solution is a toolkit that uses sales data & AI techniques to suggest the most optimal markdown, week-over-week, for each item. It uses a clear objective and a customized algorithm that predicts price markdown elasticity estimates to maximize sales season turnover.

The tool can be used manually or can run fully automated and comes with a set of dashboards that enable the team to observe and understand what is happening.

### Success

We introduced the toolkit in the setting of a controlled experiment. Such kept the cost low, yet enabled the team to prove the business case.

During the 2020 summer sales, the test case demonstrated that products for which this algorithm controlled the price had a 30% higher revenue on average, creating an 8% margin increase.

The team, therefore, decided to proceed with a full implementation of the setup.

## THE CLIENT: HOW SCHOENEN TORFS PRESENTED US WITH A MARKDOWN PRICING CHALLENGE

Schoenen Torfs is a **Belgian household** name when talking about fashion retailers. The company was founded in 1948 and grew from 4 to more than 70 stores ever since. In its mission statement, the company upholds the ambition of '*striving to be an optimistic and surprising retailer*', with core values like '*entrepreneurship, adaptability, innovation, a family feeling and honest appreciation*'.

Having regularly won prizes as a 'great place to work', the company is eager to **embrace innovation** but not without losing track of the **human factor**. Yet, it is not blind for any challenges the organization faces when it comes to profitability.

That such **profitability is under pressure** is no secret. It is a clear-cut given for any shoe retailer having to cope with new market entrants of the likes of Zalando & Amazon.

Each shoe retailer has made **the step towards e-commerce**, yet has had to cope with the high costs that come with it. Margins online are a lot smaller due to high charges such as shipping costs and return costs.

Torfs invited us to **challenge its current way of performing end-of-season discounting or markdown pricing**.

Yet, with **one caveat**. We needed to **prove the business case** of working with advanced analytics to improve its summer sales season results.


# SITUATION

## TORFS CHALLENGE OF IMPROVING THE RESULTS OF END-OF-SEASON DISCOUNTS

*An in-depth study of the situation & its challenges*

Like other retailers in the fashion industry, Torfs has had to up its game to **maintain its position** in the Belgian market. As a retail organization - having several successful digitization projects under its belt - Torfs fully subscribes to the need for further exploring new technologies and the opportunities these can bring about.

With regard to setting **end-of-season discounts or 'markdown pricing'**, Torfs' established methods are **rooted in tradition** rather than numerical analysis, due to a variety of reasons. This includes broad blanket discounts such as 'everything is now discounted by an additional x%'.

As such, the purpose of this project was to **test a new way of working** based on more advanced mathematical models. The main goal being to estimate the upward potential of such an approach and convincing the team of its merits.

From the scoping phase on, discussing the opportunities with both Torfs Buying Director & CIO, it was clear that an **experimental setup** would be essential.

An 'A/B'-test would allow all parties to observe the results, and it would help **articulate the business case** at hand.

As in any other organization subject to **change**, merely rolling out the algorithm in blind faith would undoubtedly result in "non-believers" ridiculing the algorithm.

Moreover, the cost of the current 'blanket discount' procedure is minimal. No one would be willing to risk choosing an **alternative** that hasn't proven to create a sizeable upside.

Torfs is and aims to remain a powerhouse in Belgian shoe retail. It is therefore eager to find opportunities for improvement. Embracing advanced analytics & AI in business decision-making was a straightforward manner to improve profitability without the need for significant investments or nonviable changes to current processes.

When compared to other investment opportunities, this one was **low risk and high reward.**


### TORFS' MAIN CHALLENGES

1. How can we proof to the organization that analytics-driven markdown pricing, outperforms the old method of discount/markdown pricing?
2. How can we ensure that our specific flavour of doing business, our guiding business rules are reflected in the outcome?
3. How can we set up an appropriate IT infrastructure, getting the right connections to existing systems, receive data and push changes back into the system?

## SOLUTION

# MAKING A CASE FOR ADVANCED ANALYTICS WITH A MARKDOWN PRICING EXPERIMENT

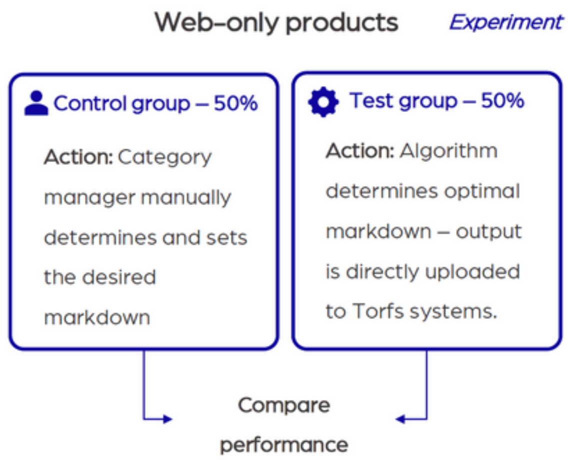
### SETTING UP AN EXPERIMENT TO PROVE THE VALUE OF ADVANCED ANALYTICS

In order to get the whole team on board, we set up an **A/B test design** where products in one group were priced by the algorithm and the other priced using traditional methods.

In this case, we chose to focus on **web-only products** because of the additional ease of changing prices for those categories. The whole web-only catalogue of different kind of shoes for different types of customers was divided between those two groups.

The experiment ran the full 2020 summer sales season, as the team could follow the progress in (near) real-time.

**Easy-to-use dashboards** show how markdowns were being executed, how the different groups were evolving over time, etc. Learn more about the **details** further on in this client case document.




**Why is it so hard to get end-of-season discounts or 'markdown pricing' right?**

READ OUR WHITEPAPER HERE

### WHAT IS THE EXPERIMENT TRYING TO PROVE?

The main hurdle retailers, such as Torfs come across when improving markdown decisions is that the process is mostly rooted in **tradition**.

However, suppose one is to look at the results of end-of-season discounts or markdown pricing. In that case, it becomes clear that results are often not what they should be due to **two returning reasons**: (i) the inability to estimate the markdown price elasticity of demand and (ii) the lack of a clear optimization objective.

Not being able to **estimate the price elasticity of demand** often means that decisions for discounts are made based on the amount of inventory remaining, the rotation & sheer gut-feeling. A retailer can obtain an accurate price elasticity estimate by using advanced analytics & AI-techniques.

Predictors (historical sales & price data, product information, etc.) can be used in machine learning models to create the best possible prediction of elasticity, later updated during the sales season using new information.

The second reason - **not having a clear optimization objective** stems from a retailers' practice to strive for proximate objectives; which are in some way related to the overall goal but are in effect misrepresentations of the actual objectives.

Where the first hurdle is addressed by applying AI-techniques to predict an accurate price elasticity estimate, the second is addressed by guiding the retailer towards the most effective objective, during the experiment.

Please find **more details** about this subject in our whitepaper on the topic.

# SOLUTION

## WHAT SERVICES DID CRUNCH ANALYTICS PROVIDE, SETTING UP THE EXPERIMENT?

### WHAT SERVICES DID WE PROVIDE?

1. Setting up a connection to Torfs' data sources
2. Training the applied algorithms using historical data
3. Creating a live test design (A/B test) on a subset of products
4. Evaluating test results & finetuning of the toolkit for a roll-out in subsequent sales seasons

Above, we listed the services we provided TORFS to get up and running. In essence, these services unburdened the team almost completely, making sure no obstacles were hindering the outcome of the experiment. **Let's take a look** at what we did in more detail.

### 1. SETTING UP A CONNECTION TO TORFS' DATA SOURCES

We created a connection to **the datasets of Torfs**, to obtain the following information: product information, historical transactions and evolutions of inventory levels. Note that we do not even need customer data, so there is no risk GDPR wise.

Whereas for Torfs, we could connect to an **existing data warehouse** this is **not an absolute necessity**. We could just as easily connect to the API of an ERP system, directly connect to underlying databases, work with periodic data dumps that are sent to our servers, etc. Getting to the data should never be much of a hindrance.

### 2. TRAINING THE APPLIED ALGORITHMS USING HISTORICAL DATA

We use the **historical data** to uncover the key patterns in terms of elasticity based on the past. Ideally, multiple years are available, but even from a single year, it is possible to get adequate estimates out of the data.

**Theoretical yield** is calculated: Prior to a live test, we calculate what would have happened if the algorithm was applied last year. This serves **two purposes.**

Firstly this gives a clear indication that the algorithm is going to work - creating some **initial faith** in the approach. Some examples can also be provided where significantly different price strategies would have been followed.

Secondly, this helps to set expectations in terms of **return on investment** from creating such a product.

Past experience indicates that **a total additional revenue between 5% and 30%** during the sales period is more or less the range where the value of the case will lie.

# SOLUTION

# WHAT SERVICES DID CRUNCH ANALYTICS PROVIDE, SETTING UP THE EXPERIMENT?

### 3. CREATING A LIVE TEST DESIGN (A/B TEST) ON A SUBSET OF PRODUCTS

A next step is to prove that the algorithm works **in practice**. To do this, we help to design **an A/B test design** where the algorithm prices products in one group and the other are priced using traditional methods.

In the selection of these groups, one can take **operational constraints** into account. In casu, we worked with the constraint of conducting the experiment **merely on web-only products**. This, due to the ease of changing prices for those categories, keeping complexity as low as possible.

The algorithm is kept as simple as possible at this initial stage. This setup enables us to have predefined structures, which we can implement at a **minimal cost**.

The goal in this first iteration is to deviate as little as possible from these forms. Naturally, if there had been **more strict rules** or constraints, these could have been accounted for.

Such may include a retailer's unwillingness to sell below specific price points, a maximal frequency for price changes, or even a minimal amount of discounted products to ensure the store attracts customers during the sale period.

### WHAT MATERIALS DID THE CLIENT RECEIVE TO PERFORM THE EXPERIMENT?

In order to perform the experiment according to the set constraints, using the current infrastructure (f.i. ERP-system), the client receives a number of specific materials.

We set up a number of dashboards that visualize the strategy and its outcomes so the client can follow the experiment in (near) real-time.

- A 'Management Dashboard' giving the category or pricing manager a general overview over the situation; providing a clear insight into the pricing at a strategic level.
- A 'Tactical Dashboard' showing information on the level of an individual product such as optimal price markdown, how the product has performed, how discounts affect sales, etc
- A simple csv-file/spreadsheet/database (customer's choice) that delivers the prices once every week, ready to upload in the ERP-system.

### 4. EVALUATING TEST RESULTS & FINETUNING OF THE TOOLKIT FOR A ROLL-OUT IN SUBSEQUENT SALES SEASONS

The end result of the experiment for Torfs was - and should in all cases be - both an **uplift** in revenue & margin for a set of the products during the first season (often just set to be 50% of products). At a **minimum cost**, the experiment proves the business case, providing the ultimate argument for rolling out the toolkit in subsequent sales seasons.

Moreover, the experiment has a second benefit. It shows what actions can remain **manual,** performed by a human decision-maker, and what actions can be **automated**. This is automation in the strict sense of the word meaning that there are little to no human-interactions needed to change these price markdowns to their optimal values. For some retailers, the most straightforward next step is to make the whole process robust for the **roll-out in subsequent seasons** and stop there.

For others, **further steps** can be taken. These mainly relate to taking more strategical and operational constraints into account. Or one may be interested in applying more advanced optimization kernels to boost performance.

All this comes down to building **an advanced version** of the toolkit as a result of co-development between the retailer (who asks questions, proposes ideas based on observations during the season) and Crunch Analytics.

# SOLUTION

## HOW DID TORFS EXECUTE, MONITOR AND EVALUATE THE EXPERIMENT?

### CRUNCH ANALYTICS AS A TRUSTED ADVISER

With the main aim of the experiment being to demonstrate the value of advanced analytics in business decision-making with regards to markdown pricing, we created **an environment that instils trust**.

One that would allow the team at Torfs to execute markdown price suggestions swiftly, to **observe** what is happening and **understand** how these price suggestions take into account the strategic ruleset defined before the start of the experiment.

That is why we ensured that everyone around the table thoroughly understood what we were doing, an appropriate sequence of **follow-up** and **advisory meetings** was agreed upon, and two easy-to-use **dashboards** were set up that would allow Torfs to monitor the situation first-hand.

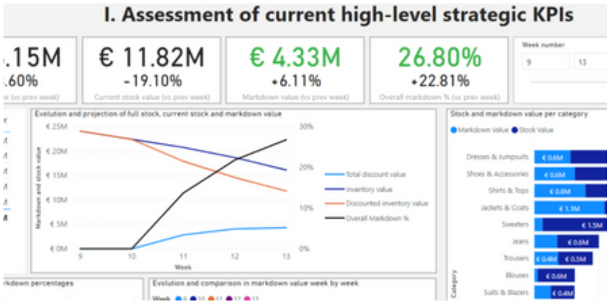

### WHAT WAS THE PROCESS LIKE FROM THE CLIENT'S PERSPECTIVE?

As described in the previous section, Crunch Analytics provided a comprehensive set of **services** to connect to the client's data sources, find key patterns in terms of price elasticity based on previous sales periods and train the markdown pricing algorithm accordingly. An algorithm that is further refined during the actual sales season, using the input of more recent information.

Once the **sales season** starts, **a week-over-week sequence** kicks off. Last week's sales information is downloaded and validated. Based on the demand observed in that week, the markdown pricing algorithm updates the price elasticity estimates and calculates new optimal price markdowns for the upcoming week.

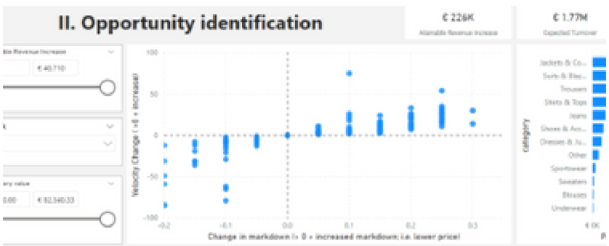
This and additional information is displayed in **two dashboards** that enable follow-up and should instil trust in the process.

The first is a **'management dashboard'** giving the category or pricing manager, a general overview of the situation. How are we doing in general? How much are we discounting? How are they distributed across different product categories? What are the trends? How are clients responding?




Glimps of a dummy 'Management Dashboard'

The second dashboard is a more **'tactical dashboard'** showing information on the level of an individual product such as optimal price markdown, how the product has performed, how discounts affected sales, etc. It allows the category/pricing manager to take into account the suggested price markdown for a given product and evaluate it. The dashboard also indicates **priorities**, helping that same person to focus on the products where the potential for additional revenue is the greatest. If all is validated, the output can be easily uploaded via csv-file/database/other to the client's ERP-system.




Glimps of a dummy 'Tactical Dashboard'

The best part of it all is that this whole sequence can be **partly/fully automated**, making the category/pricing manager an observer of the process, able to spend more time focusing on strategic analysis and discussion of results.

# SUCCESS

*Situation, Solution & Success*


### WHAT WAS THE OUTCOME OF THIS MARKDOWN PRICING EXPERIMENT?

As we described, the main goal was to **prove the business case** of embracing advanced analytics to improve end-of-season discount pricing. To prove that it can yield better results and ensure the tasks related become less time-consuming.

In ten weeks, the algorithm determining the optimal markdown for web-only products achieved **a 30% increase in revenue**, while keeping the average markdown level under control. Such resulted in **an 8% increase in margin**.

This is a tremendous difference, yet it is **not that uncommon**. As humans, we are often more conservative in making harsh or challenging decisions. Moreover, the algorithm was able to take much more parameters into account, enabling it to run according to a more fine-grained strategy.

### HOW CAN THE RESULTS OF THE EXPERIMENT BE USED IN FUTURE SALES SEASONS?

In a **next step**, the entire toolkit can be made more robust to be able to cover the **whole catalogue** in **upcoming seasons**. As such, it can become an integral part of Torfs' pricing process.

Yet, one can also **further customize** as no retail activity is alike. Some retail organization experience in-season demand erosion which-might result in sub-optimal decisions. Changes can be made to cover this situation.

Other retailers struggle with the difficulty of physically implementing price changes, week-over-week. Such is an additional constraint which can be accounted for. From a performance point-of-view, one can make use of more advanced kernels, expanding possibilities even more.

> "The client was, of course, pleasantly surprised by the achieved results. Creating 30% of additional revenue in an experimental setup at a reasonable price point was certainly above expectations.
>
> Moreover, the fact that we went from kick-off to go-live in under three weeks was a much applauded given. The fact that we were able to prove the business case, and demonstrate that the impact on the team is limited, opened the door for further collaboration."

**LAURENT MAINIL**
Co-founder & CEO

CLIENT STORY

# CAN WE HELP YOU TOO?

Are you interested in our help to improve your markdown pricing? **We are still taking on clients for the winter sales season of 2020**. These projects work with a minimal setup fee to set up connections, and a fixed license fee that is only payable if the first experiments are successful and usage of the tool is continued. **Do get in touch!**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