# Webscraping prices to estimate hedonic models and extensions to other predictive methods

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# 01 Context

# Price collection for electronic goods in France

- Data collection is performed manually, in physical stores and on the Internet
  - Representativity of different types of stores matters: geographic stratification involves 1pt difference on the CPI from december to april
- We use a fixed basket
- Webscraping is a very interesting source of data, especially for this type of goods:
  - More and more products are sold on the Internet
  - Detailed information on the products, lower cost of collection
- Experiments have been lead on webscraping, mostly for transports
  - Automatic data collection is in production for airplane tickets and maritime transportation
  - We still have to set a general organisation and infrastructure for further use of webscraping in production → we will first use **manually collected data** with models estimated with webscraped data

# Hedonic models and innovative goods

- Importance of taking innovation into account, because it is a major driver of prices
  - New types of products
  - New technical characteristics
  - Improvement of technical characteristics
  - Impact on the price of products already on the market

- Hedonic models can help us measure the technical improvement of electronic goods

- Hedonic re-pricing is preferred in France, and currently in use for household products, because:
  - Easier to check the robustness of the model
  - Fewer statistical analysis are needed
  - For webscraping, no need to have a production infrastructure, only need to gather data at the base month

# Goal: using webscraped data efficiently to estimate the difference in quality

- This involves :
  - Getting data from the websites
  - Cleaning data: from raw data found on the description pages to data sets which can be used for statistical needs
  - Extracting relevant information from these data sets
  - Estimate the price of the good from its technical characteristics → hedonic models, or any type of predictive method
- Hedonic repricing will be used to adjust the base month price:
  - $P_0'(X_k) = P_0(X_k).f(Y_k)/f(X_k)$, where f is the quality function linking the technical characteristics to the price
  - log(f) is linear in the hedonic regression case, but we could use other prediction methods

# 02

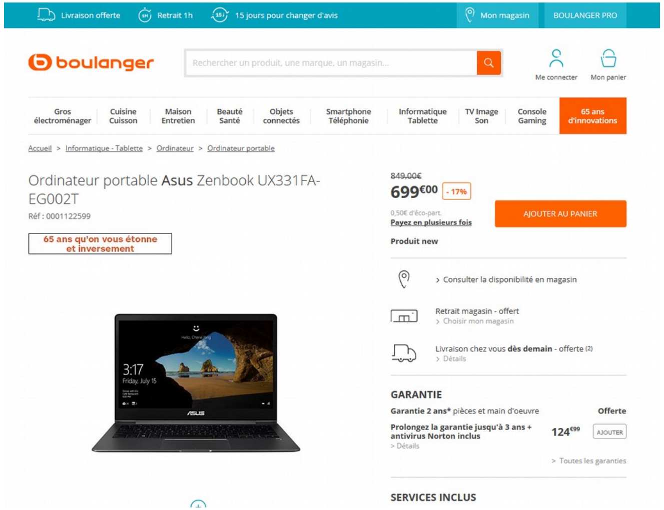
# Data collection and treatment

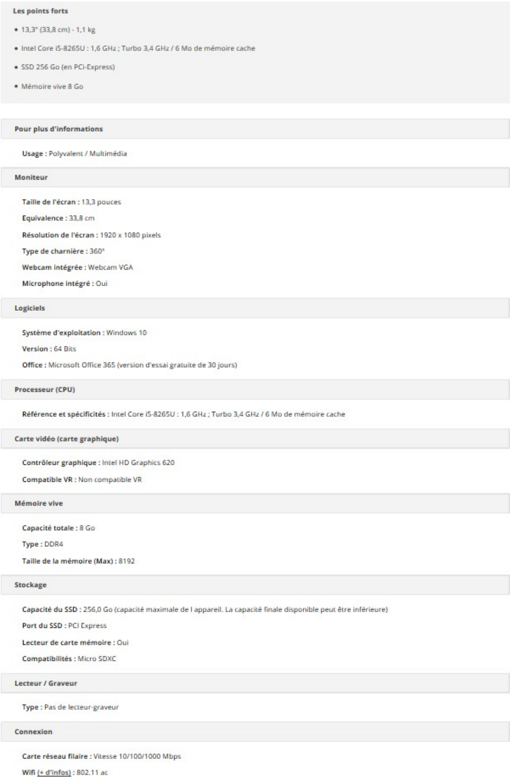
# Data collection

- Data was webscraped from four ecommerce websites; the detailed product page provides information on the technical characteristics

- Scraping was done in Python by statisticians; we still need to figure out how to organise the work between stat and software teams if we do webscraping in production

- Each website has a common page structure for all types of goods, which limits the development costs



# Cleaning data

- We get raw data, we must first transform them to make them useable:
  - Remove technical characteristics with too many missing values
  - Harmonise the format, the levels of discrete variables, the units for continuous ones, transform text into numbers, etc.
  - Detect anomalies
  - Imputate missing values

→ webscraping can make it easier to get data for many types of products, but
  - We have to set a general canvas of treatment
  - We must adapt it to the specificities of each product → modularity

- We have to be careful because some websites mix their products with other sellers, or mix new and repackaged products
  - Some categories even contain a few products which have nothing to do with the other ones!

# Many information on the website… what is relevant ?

- There are many technical characteristics available, but our price collectors will not be able to collect them all

- Even in the case of webscraping in production, we want to limit the number of variables in the case of hedonic models,

- → We have to select the ones which can predict the price
  - Using sectorial expertise/intuition can be a first step
  - Automatic selection through statistical analysis can be more efficient, especially if we want to apply it to many products

# 03 Variable selection and price prediction methods

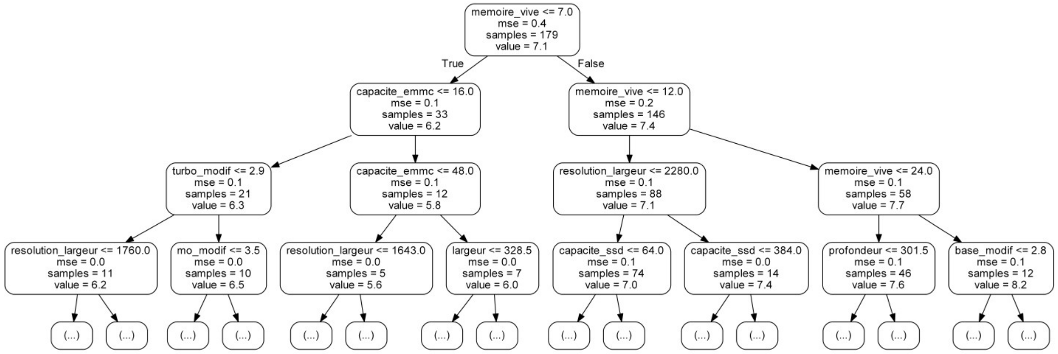
# Variable selection and price prediction



- We want to select a subset of our variables…
- We also want to predict prices with the technical features of the good

→ some statistical learning tools do both!

# Random forests




- Decision trees split the data set at each node, into subsets minimizing the intra-classes variances
- The most relevant features are at the top
- At the bottom of the tree, each cell makes a prediction for observations satisfying conditions of each of the upper nodes (*e.g.* screen size < *15 inch)*
- Among tree-based methods, random forests average several estimators, each one coming from a sample of the original data (sampling observations and variables)
- We can cut the tree at a defined level to get only the most influential nodes
- The trees can be used for prediction, variable selection and variable transformation

# LASSO regression

- LASSO (least absolute shrinkage method) is a regression with penalization of the coefficients

$$\min_{\alpha_1,\ldots,\alpha_p} \sum_{i=1}^{n} (y_i - \alpha_0 - \sum_{j=1}^{p} \alpha_j x_{i,j})^2 + \lambda \sum_{j=1}^{p} |\alpha_j|$$

- The L1 penalization cancels some coefficients, as opposed to the ridge regression (L2)
- We can choose to have more or less non-zero coefficients by making λ vary
  - For prediction purpose, we prefer to use **cross-validation**

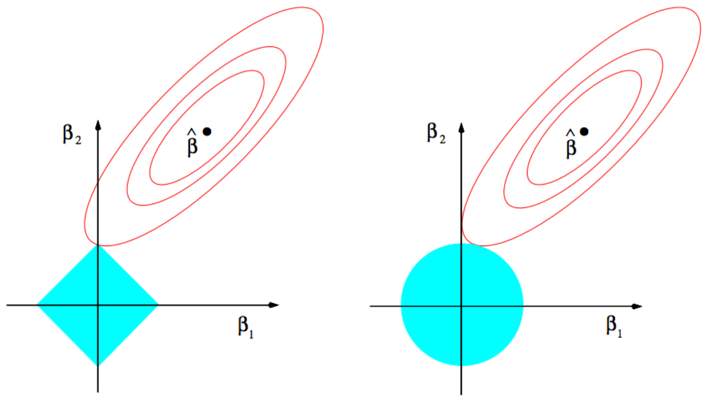



**FIGURE 3.11.** *Estimation picture for the lasso (left) and ridge regression (right). Shown are contours of the error and constraint functions. The solid blue areas are the constraint regions* $|\beta_1| + |\beta_2| \leq t$ *and* $\beta_1^2 + \beta_2^2 \leq t^2$*, respectively, while the red ellipses are the contours of the least squares error function.*

Source: Hastie, Tibshirano, Friedman, *Elements of Statistical Learning*, Springer

# Results for variable selection

- Random forests show that for laptops, the RAM is the most relevant feature (importance around 73% in the trees), followed by the frequency (base and boost) of the processor
  - Other variables selected: dimensions, cache size, weight, resolution, screen size, brand (Apple)

- Random forests provide more stable results (with respect to the website and the collection date) than LASSO

- AIC or BIC stepwise selection could also be used

# Prediction

- Predictive approach :
  - Define a training set, to be split in to subsets in the case of cross-validation
  - Compare models using :
    - **mean squared error**
    - **mean average error**
    - **accuracy = 1 – MAPE** (mean average percentage error) → easier to use

- RF can predict the price with an accuracy around **85%**
  - Up to **89%** if we include the model of graphics card, but difficult to use when new models appear

- LASSO has lower accuracies

- These models usually perform better on the log of price (but we always evaluate the prediction on the price)

# 04 Hedonic replacements

## Use of hedonic models

- We want to reprice our product at base month, using :

$$P_{j,t=0} \cdot \frac{f(X_k)}{f(X_j)}$$

where *j* denotes the replaced product, and *k* the replacing product, and *f* is the function:

$$\exp(a + b_{1.}\, x_1 + b_2 . x_2 + \ldots + b_n . x_n)$$

coming from the model :

$$\log(P) = a + b_{1.}\, x_1 + b_2 . x_2 + \ldots + b_n . x_n + \varepsilon$$

- We plan to apply the model to data collected in stores
  - → we assume that the difference in quality has a comparable effect on the price of different stores, even if the products are priced differently in the different stores

## Use of hedonic models

- Linear models provide good accuracies, around 84%
- Accuracy drop when we combine data from different websites
- R-squared > 0.9
- On the webscraped data, price change estimates were computed using bridged overlap and these hedonic models → results are close, work to be continued throughout the year!

| | March/January with basis month = January | April/March with basis month = March |
|---|---|---|
| Bridged overlap | 95.8 | 98.3 |
| Hedonic model | 96.3 | 98.5 |

# 05 Conclusions and further work

# Conclusion



- Webscraping can provide detailed information about technical characteristics, and help us estimate hedonic models

- Statistical learning models, such as random forests, can be useful for selecting relevant variables quickly
  - → quickly expand the scope of hedonic models to many products, without too much analysis

- They can perform better than traditional hedonic models and could be interesting to use, combined with webscraping in production
  - However, the gain in accuracy is not very important
  - **Possible bias**?

# Some ongoing developments include:

- Testing our models over a longer period
- Using random forests and LASSO predictor to adjust for quality, and compare them to the log-linear model and to (bridged) overlap
- Testing generalized additive models with cubic splines
- A better treatment of missing values (stratified hotdeck)
- Outlier detection → estimating the models without aberrant observations, and selecting replacing products more carefully
- Extension to other electronic goods

# Thanks for your attention !

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