Ask anything

yo chat give me a list of laptops with these specifications

bro no something within a reasonable price range

ok but which ones better in terms of what i want

### We'Ve cot abetter solution than chatelot



### ANOVERVIEW

Ever wish you had a genie who could instantly tell you the price of your dream laptop and show you the best match in the market?

We deliver three core ML functions:

- Descriptive: K-Means Clustering to segment computers based on price, RAM, and other specs. PCA is a way of showing the clusters of the K-Means
- Predictive: LightGBM Regression to estimate prices from user inputs
- Prescriptive: K-Nearest Neighbors (KNN) to recommend similar listings with ranked similarity

### COLLECTIO

- CSV file: 8,064
   marketplace listings
   (rows) x 135 raw Spanish-language columns
- Encoded in UTF-8-SIG
  with mixed metrics,
  units, and labels; .CSV file
  with 135 columns.
- No scraping or APIs; data ingested directly via pandas.read\_csv.

### RAW DATA

### CLEANED DATA

1. Dropped Duplicates →

df.duplicated().sum()

- 2. <u>Standardized Column Names</u> with custom slugify function
  - → removed accents, lowercase, dropped stopwords (e.g., Pantalla\_Tamaño → pantalla\_tamano)
- 3. <u>Dropped Unnamed Columns:</u>
  - df.drop(columns=['unnamed\_0'])
  - Full null or >70% null columns



#### 4. Price Normalization

- Parsed "Precio\_Rango" (e.g., "1.026,53 €
   2.287,17 €") into:
- precio\_min, precio\_max, and precio\_mean
- <u>Dropped original string after parsing</u>

### 5. Numerical Extraction

- Created functions to extract float from strings (e.g., RAM, CPU speed)
- Remove thousands separators.
- Apply apply\_cleaning\_to\_column()
   across many dirty fields

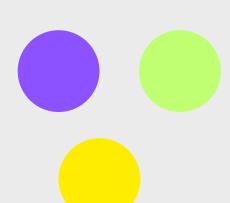
#### 6. Standardized Screen Resolution

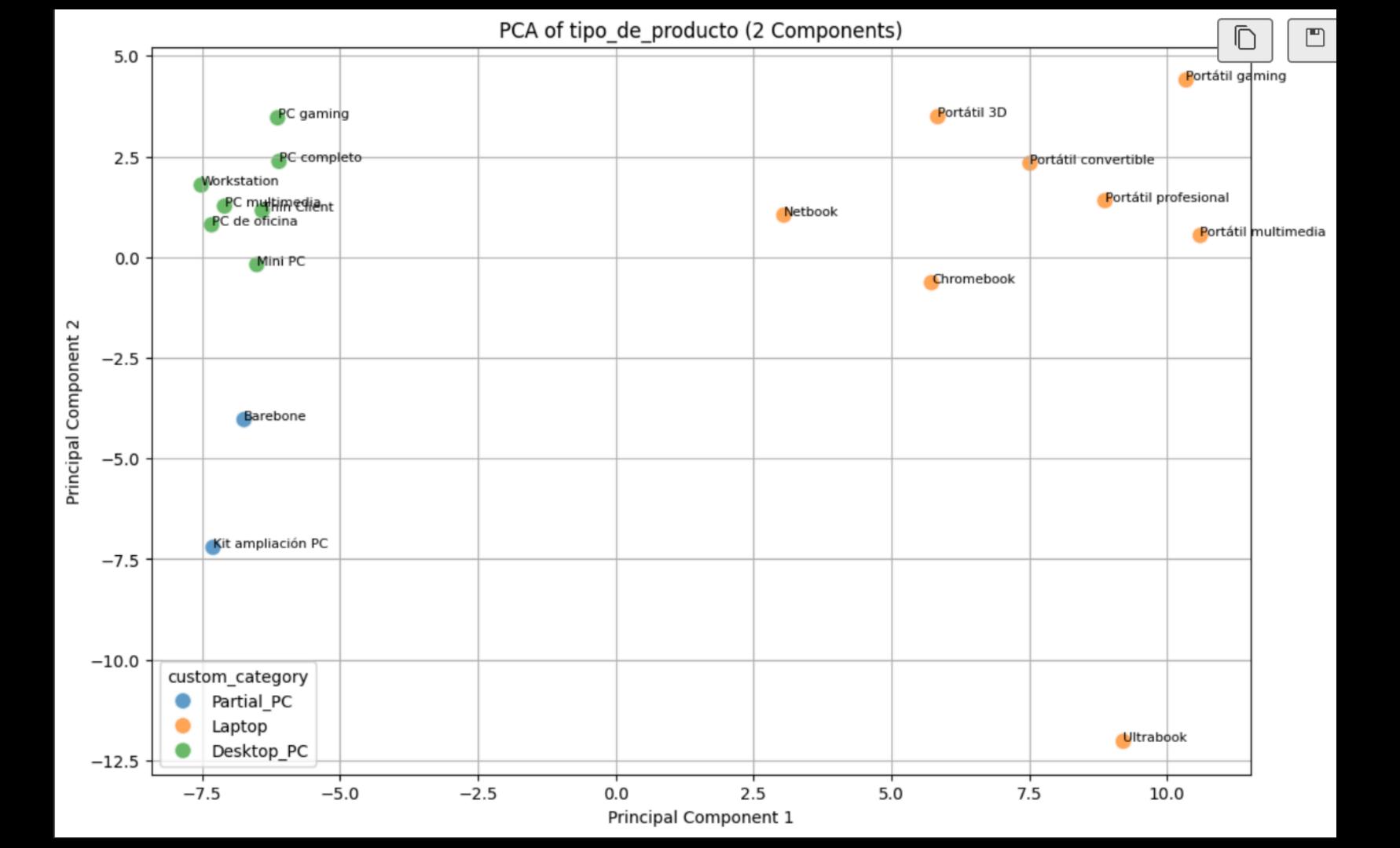
 Used regex to convert inconsistent resolution strings to "WIDTHXHEIGHT"

E.g., "4K (3.840 x 2.160)" → "3840x2160"

### 7. Offers Cleaning

 Convert strings like "200 ofertas" to 200.0 (float) for numeric ops.



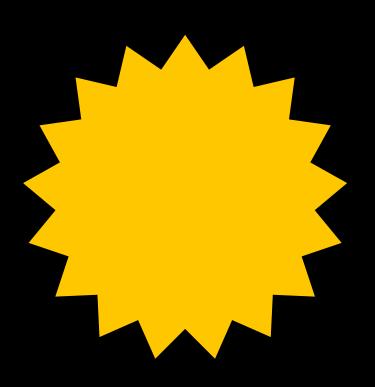


# HANDLIN( MISSING ' DATA

Aware of Missing-Not-At-Random (MNAR) issues (e.g., screens missing in desktops). To solve, we handled it by isolating category-specific structures and then:

Used df.isnull().sum() and missingno

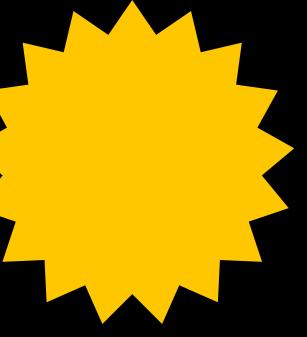
heatmaps



### STRATEGY?

70% missing: <u>dropped</u>

- 30–70%: conditional imputation or dropped
- <30%: imputed by product category using mean/mode</li>



# FEATURE ENGINEERING & SELECTION

### HALL OF FAME

FEATURE ENGINEERING & SELECTION

٦

ONE-HOT ENCODING

for low-cardinality categorical fields.

2

ORDINAL ENCODING

for ordered features like processor generation

CATEGORICAL HANDLING

3

PCA &
CORRELATION
ANALYSIS

PCA to retain
features explaining
90%+ variance
+ Removed highly
correlated
variables
(Pearsons).

4

FINAL MATRIX

Final feature matrix optimized for model performance & interpretability. MEAN PRICE: Extracted from raw price range string

def process\_price\_range(price\_str)

Volume (cm³)= height x width x depth

Category Mapping: Mapped devices to English Classes (Ultrabook, Tower, All-in-One)

### FEATURE ENGINEERING

# MODEL TRAINING & VALIDATION

TECHNICAL APPROACH FOR SOLVING FUNCTIONALITIES

### DESCRIPTIVE

### K-MEANS CLUSTERING

- Business value: clustering different product segments.
- **Inputs:** features in the df\_engineered.csv dataset.
- Output: k=2 clusters.
- Evaluation: PCA dimensionality reduction for visual inspection of clusters, plotted clusters and tipo\_de\_producto feature against same principal component axes.

### PREDICTIVE

### LIGHTGBM REGRESSION

- Business value:
  - Price prediction of computer given user selected specifications.
  - Feature importance on price of computer.
- Inputs: features in <u>df\_engineered\_desktop\_pc.csv</u> or <u>df\_engineered\_laptop.csv</u>.
- Output: predicted price and feature importance.
- Target: precio\_mean feature.
- Validation: cross-validation hyperparameter tuning.
- Evaluation: RMSE ≈ 520 EUR, R<sup>2</sup> ≈ 0.81.

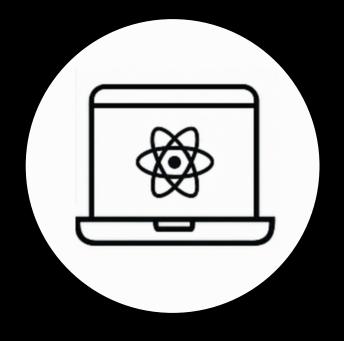
### **PRESCRIPTIVE**

### K-NEAREST NEIGHBORS

- Business value:
  - K-similar product offers to user selected specifications.
- Inputs: features in <u>df\_engineered\_desktop\_pc.csv</u> or <u>df\_engineered\_laptop.csv</u>.
- Output: k=5 neighbours.
- Evaluation: KNN regressor perdicted versus target price scatter plot and residual plot as baseline performance metrics.

### APP ARCHITECTURE & DEPLOYMENT

### FRONTEND STACK



REACT-BASED UI

### BACKEND APIS

PYTHON: SCIKIT-LEARN PANDAS, MATPLOTLIB

FOR THE EDA & TRAINING





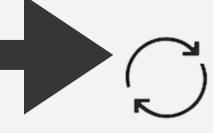
API HOSTING: DEPLOYED VIA GIT HUB -> GOOGLE CLOUD RUN FUNCTIONS



ML MODELS: LIGHTGBM, KMEANS, KNN IN PYTHON (JOBLIB SERIALIZED)



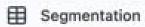
MODEL STORAGE: GOOGLE CLOUD STORAGE



CI/CD AUTOMATION: GITHUB ACTIONS - TRIGGERED ON PUSH TO MAIN FOR THE MODELS

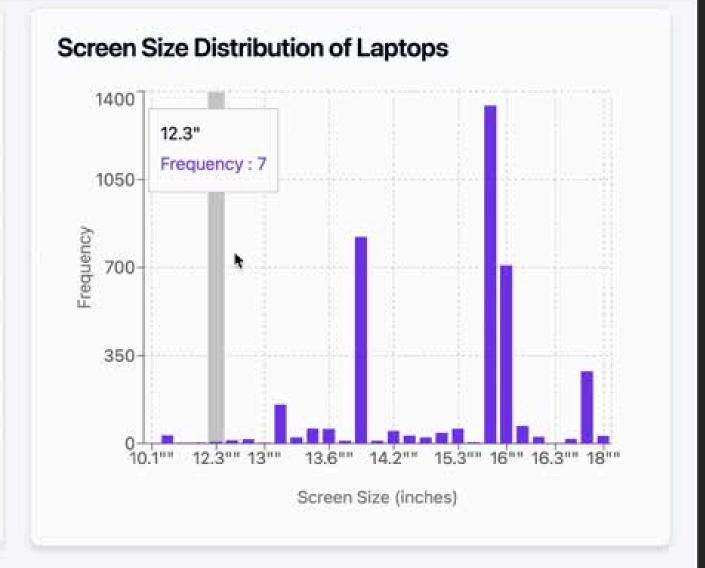


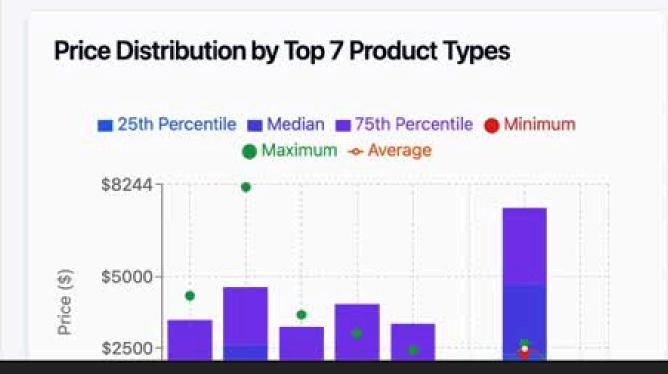


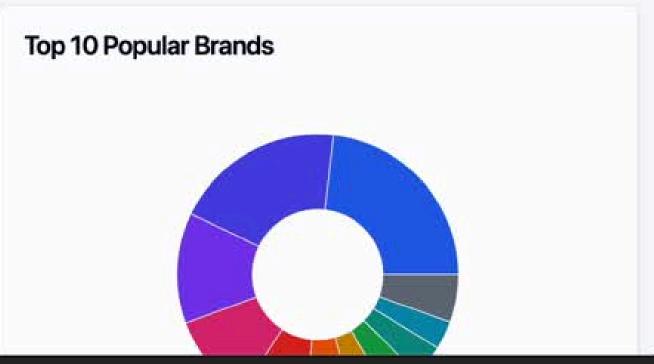


∠ Prediction









## IMPROVEMENTS 8 NEXT STEPS

### GENIE'S NEXT EVOLUTION

- Live data integration via APIs to keep listings up to date
- Prediction confidence intervals to show uncertainty
- User-based personalization using historical preferences
- Model retraining via feedback log ingestion
- Multilingual toggle to support Spanish/English Uls
- Domain expansion to peripherals, monitors, GPUs
- Feature Feedback to allow for constant improvements
   of model & the display of processed data.

# THANK YOU