

### **ROBO-REVIEWS**

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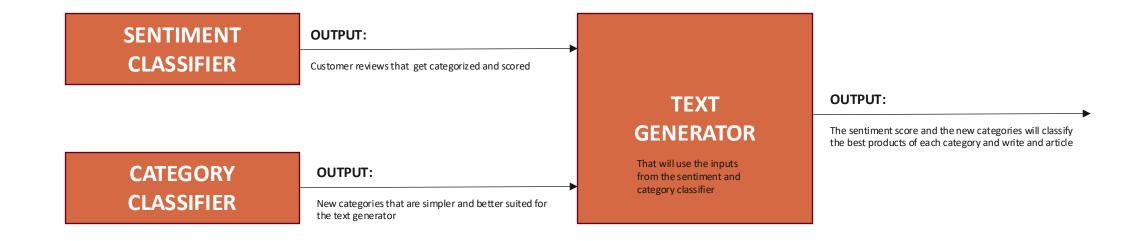


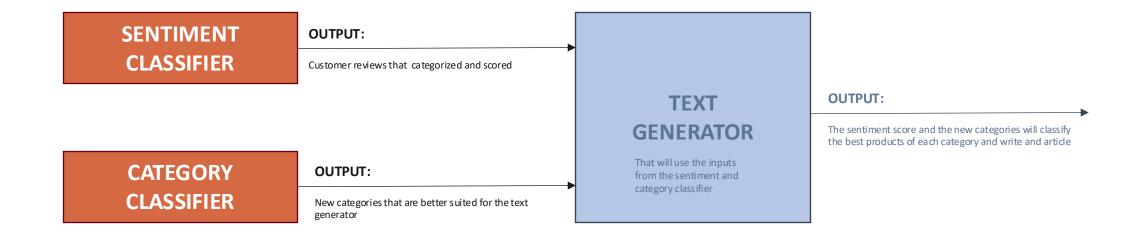


### 1.- PROJECT OVERVIEW

- Used NLP techniques to classify consumer reviews by sentiment (positive, neutral, negative) and grouped products into broader categories. I also tried to identify the top 3 best and worst products per category based on sentiment and ratings..
- FINAL MODELS → Electra\_discriminator / all-MiniLM-L6-v2 / And...

• Why this is awesome? It automates insights from large datasets, helps with decision-making, and provides quick, user-friendly product summaries for smarter shopping. If it worked properly...





#### **REALITY**

SENTIMENT OUTPUT:

CLASSIFIER Customer reviews that categorized and scored

CATEGORY OUTPUT:

CLASSIFIER New categories that

New categories that are better suited for the text generator  $% \left( 1\right) =\left( 1\right) \left( 1\right)$ 

The amazon echo show alexa-enabled bluetooth speaker with 7" screen has received some criticism from customers. Here's why they don't recommend it: not ery ancy ut not ow If ou ave am Am Am Am Am Am Am...

Review: This is the worst product ever. Do not buy it. Predicted

Sentiment: **negative** 

Review: Not a bad product but not great either Predicted Sentiment:

positive

Review: Im in love with this tablet. Predicted Sentiment: positive

Review: Just an ok product, not good but not bad. Predicted Sentiment:

neutral

Review: I think this is not a good product at all. Predicted Sentiment:

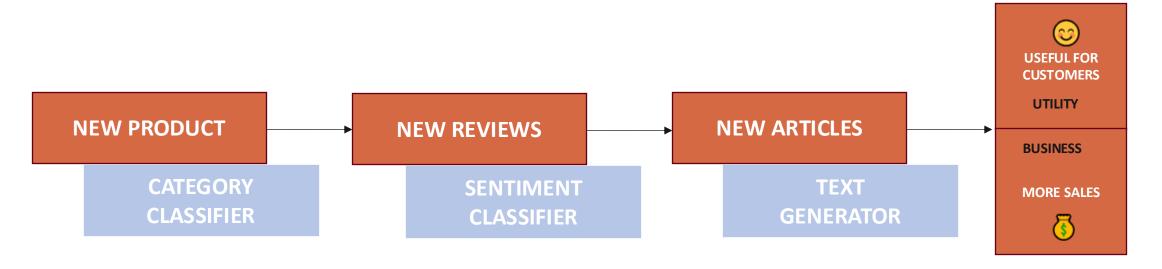
negative

Review: I'm going to ask for a refund, I'm not satisfied. Predicted

Sentiment: **negative** 

### 4.- INTRODUCTION

- If it worked, it would have ben useful to get a quick overview of a best product of a category without having to read tons of reviews.
- This solution is implemented through NLP methodology, which combines sentiment analysis, category
  grouping, and text generation using transformer models to classify reviews and generate product summaries.



### 5.- PIPELINE - DATA

#### **DATASET**

# SENTIMENT CLASSIFIER

# **CATEGORY CLASSIFIER**

#### **TEXT GENERATOR**

Sparse categories

- Missing values
- Useless columns
- Sparse categories
- Unbalanced

- Lowercasing
- Punctuation
- Oversampling
- Naan
- Stemming
- Lemmatizing
- TOKENIZATION

- Lowercasing
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new\_categories

sentiment\_score

Implemented

Tried but worked worse

Tried but didn't work

# **5.- PIPELINE - TECHNIQUES**

**DATASET** 

# SENTIMENT CLASSIFIER

- 3 LLMs
- Fine tuning

# **CATEGORY CLASSIFIER**

- Kmeans
- LDA
- LoReg
- 2 LLMs
- Fine tuning
- Manual labeling

#### **TEXT GENERATOR**

- new\_categories
- sentiment\_score

### 6.- SENTIMENT ANALSYSIS MODEL

#### Preprocessing

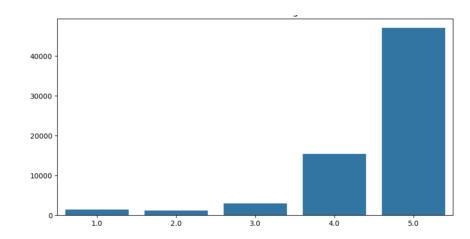
 Selectively remove Naan, lowercase, tried oversampling for negative feeling but was impossible.

#### LLMs:

- BERT → High Accuracy, but really heavy on computing.
- DistilBert → A bit faster than BERT but failed in accuracy but much faster.
- Electra\_Discriminator → Good Accuracy (almost like BERT) but much faster.

#### Implementation:

 Trained over review\_text for fine tunning and used ratings as a validations dataset. And fine tuned the over training. 2 Epochs, drop & learning rate

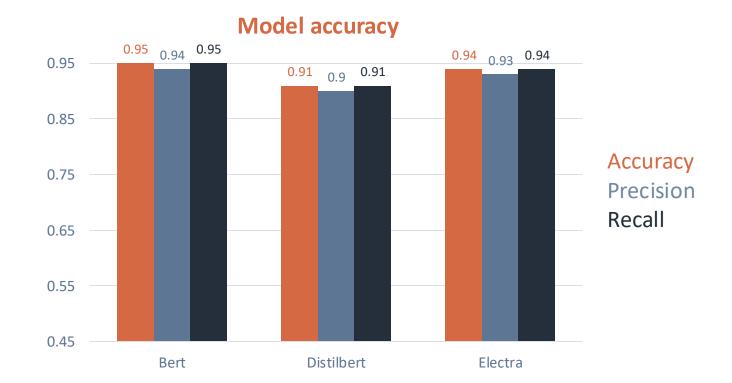


### 6.- SENTIMENT ANALSYSIS MODEL

#### **EVALUATION**

#### **E**valuation:

• Inference with examples out of the dataset and random samples of the dataset. Classic evaluation metrics F1, accuracy etc.



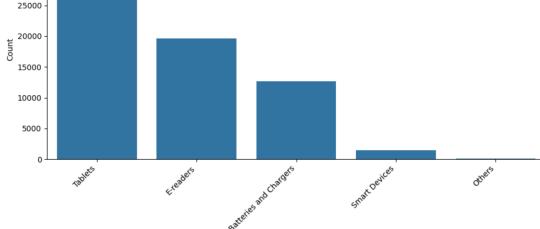
### 7.- CATEGORY CLASSIFICATION MODEL

#### Preprocessing

- Tokenize data, configurated max length and batch size.
- Tried lemmatization and stemming but didn't work.
- Everything started to work after I used custom 'manual' mapping on the categories column.

#### LLMs:

- Electra\_Discriminator → Didn't performed as well as with sentiment analysis specially because I used it with the clustering technique that didn't worked very well.
- all-MiniLM-L6-v2 → More or the same in terms of speed and Accuracy.



Distribution of New Categories

35000

30000

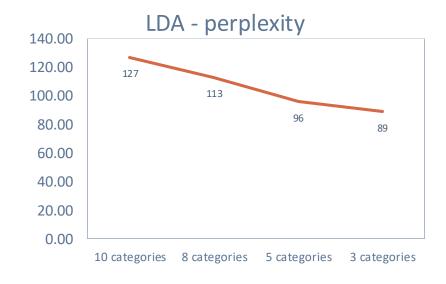
- Implementation and fine tunning:
  - Same approach that with sentiment but using custom mapping instead of ratings.

### 7.- CATEGORY CLASSIFICATION MODEL

**EVALUATION** 







#### **E**valuation:

• Inference with random samples of the dataset of the name column. Classic evaluation metrics F1, accuracy etc.

### 7.- CATEGORY CLASSIFICATION MODEL

#### **EVALUATION**

Product Name: Fire Tablet, 7 Display, Wi-Fi, 8 GB - Includes Special Offers,

Magenta

Predicted category: Tablets

Product Name: AmazonBasics AA Performance Alkaline Batteries (48 Count) -

Packaging May Vary

Predicted category: Batteries and Chargers

Product Name: Amazon Fire Tv,,, Amazon Fire Tv,,, Predicted category: Home

**Electronics** 

Product Name: AmazonBasics AAA Performance Alkaline Batteries (36 Count)

Predicted category: Batteries and Chargers

Product Name: Amazon Kindle Paperwhite - eBook reader - 4 GB - 6 monochrome

Paperwhite - touchscreen - Wi-Fi - black,,,

Predicted category: E-readers











### 8.- TEXT GENERATOR

#### Preprocessing

• Created a new dateset based on the "new\_categories" and "sentiment", in an ideal a would have implemented nother column with sentiment score but had Colab problems.

#### Implementation:

**TE-RRI-BLE.** Left it to focus on the two previous models.

### 8.- TEXT GENERATOR

GPT 2 Says:

.....

T5 Small Says:

"not ery ancy ut not ow If ou ave am Am Am Am Am Am Am Am.."



### 9.- TAKEAWAYS

- Need better planning from my side.
- Implement sooner manual inference to check the results as classical metrics could "lie".
- Don't try many things in big projects grab one and make it work.
- Define clearer goals.
- Use cloud computing resources wisely (spend 34€ this week in Colab).
- Save frequently.

# Thank you