

The background of the slide is a collage of coffee-related images. In the top left, a woman with curly hair holds a white coffee cup and a smartphone. In the top right, a white cup of coffee sits on a surface surrounded by coffee beans. In the bottom left, a pair of hands holds a large quantity of red coffee cherries. In the bottom right, a smiling man in a striped apron is shown from the waist up. The entire collage is overlaid with a dark blue geometric pattern consisting of large, overlapping, rounded shapes.

**LAVAZZA**

TORINO, ITALIA, 1895

# Leveraging Large Language Models for Marketing Analytics



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# Project Value Proposition

For **marketers** seeking deeper **insights** on product launches, our **analytics software** transforms raw online comments and reviews into **actionable metrics**.





## Project Goal



Developing **AI software** to accurately assess the **real impact of a product launch** by analyzing **consumer sentiment** across social media **comments** and third-party **reviews**.

**Sustainable Development Goal:**



Responsible  
Consumption  
and Production



# Hypothesis



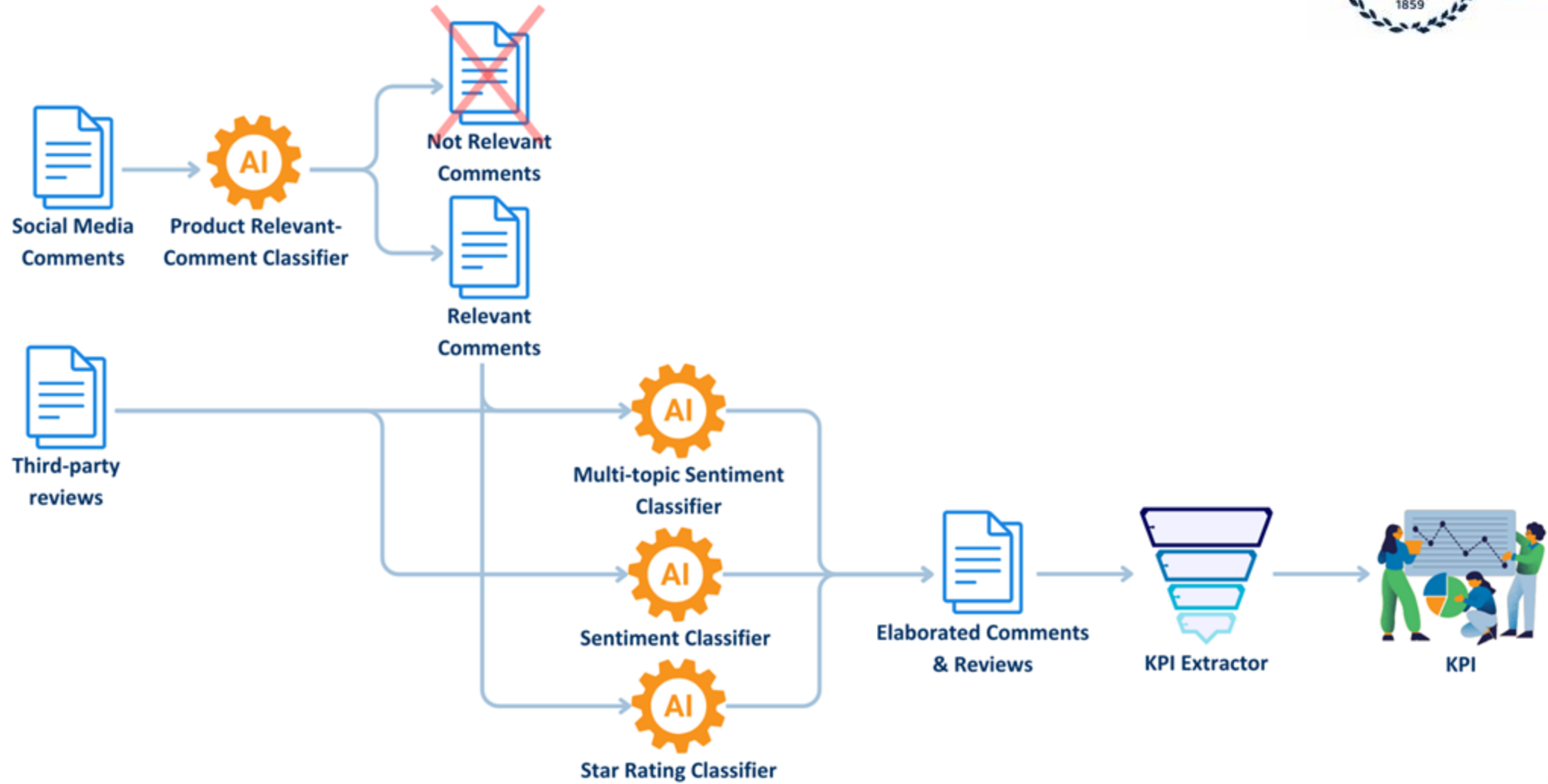
**Large Language Models** can be effectively used to extract valuable insights from consumer comments and reviews to enhance marketing strategies.

**Specifically:**

- LLMs can effectively identify **product-relevant comments**.
- LLMs can extract **key product aspects** from reviews and comments and assign **appropriate sentiments** to each.
- LLMs can successfully assess **sentiment** in comments and assign **rating stars** to reviews.



# Method - Pipeline







# Method - Classification Block and Models



The **core** of the pipeline is the **classification block**, responsible for all classification tasks. Its structure adapts to the **model type** used:

- **General-Purpose Models (Chat-like LLMs):** Flexible and versatile for various tasks.
- **Specialized Task-Based Models:** Fine-tuned for specific tasks, offering higher precision in narrow domains.



# Method - General Purpose Classification Block

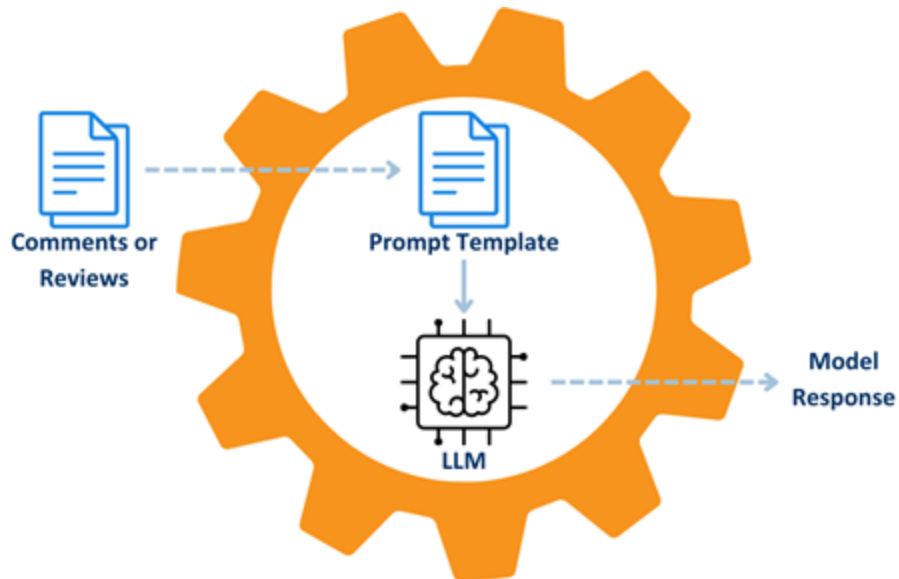
The general purpose classification block comprises **two main components**:

## Prompt Template:

- Clearly defines the **classification task**.
- Includes **examples** (few-shot prompting only).
- Specifies the **structured output format** for consistent model responses.

## General-Purpose Model (LLM):

- **Processes the task-specific prompt** (combining prompt template and input data).
- Generates **task-specific responses**.







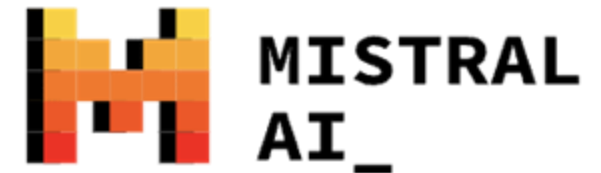
# Method - General Purpose Models



**Gemma2:** large language model from Google, different versions: 2B, 9B and 27B



**Llama3:** large language model from Meta, 8B, 70B and 405B

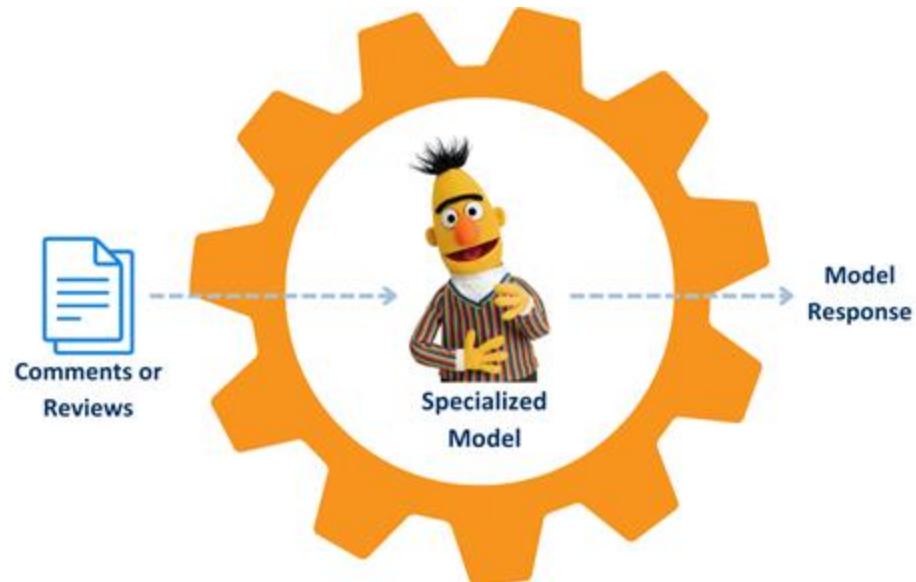


**Mistral:** large language model from Mistral AI



# Method - Specialized Classification Block

The specialized model classification block comprises **two main components**:



**Specialized BERT-base Model:** Takes reviews or comments as input and generates a response based on the specific task.



# Method - Specialized Models



- **Sentiment Classification**
  - *distilbert-base-multilingual-cased-sentiments*
  - *twitter-xlm-roberta-base-sentiment-finetuned*
  - *twitter-roberta-base-sentiment-latest*
- **Star Rating Prediction**
  - *bert-base-multilingual-uncased-sentiment*
  - *multilingual-sentiment-analysis*

\*from Hugging Face



# Method - Prompting Approach

## Zero-shot:

The model predicts the answer given only the description of the task in natural language.

- 1 Translate English to French: ← *task description*
- 2 cheese => ← *prompt*

.....



# Method - Prompting Approach

**Few-shot:** The model sees a few examples of the task.

1	Translate English to French:	← <i>task description</i>
2	sea otter => loutre de mer	← <i>examples</i>
3	peppermint => menthe poivrée	← <i>examples</i>
4	plush girafe => girafe peluche	← <i>examples</i>
5	cheese => .....	← <i>prompt</i>



# Experiments - Data



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**Data  
Sources:**



**Wonderflow**



**Digimining**



**YouTube**



**Instagram**



**Generative  
Models**

**Datasets:**

**Reviews**

**Comments**

**Synthetic  
Data**





# Experiments - Datasets



## Reviews:

- Records: **2930**
- Sampled records: **500**
- **Star Rating** label ration: **100%**
- **Multi-Topic Sentiment** label ratio: **95%**
- **Tiny Eco** Reviews: **79**

## Comments:

- Records: **577**
- **Labelled** Comments: **0%**
- **Tiny Eco** Comments: **77**

## Synthetic Data:

- **Comments** Records: **236**
- **Reviews** Records: **500**
- **Labelled** Comments and Reviews: **100%**

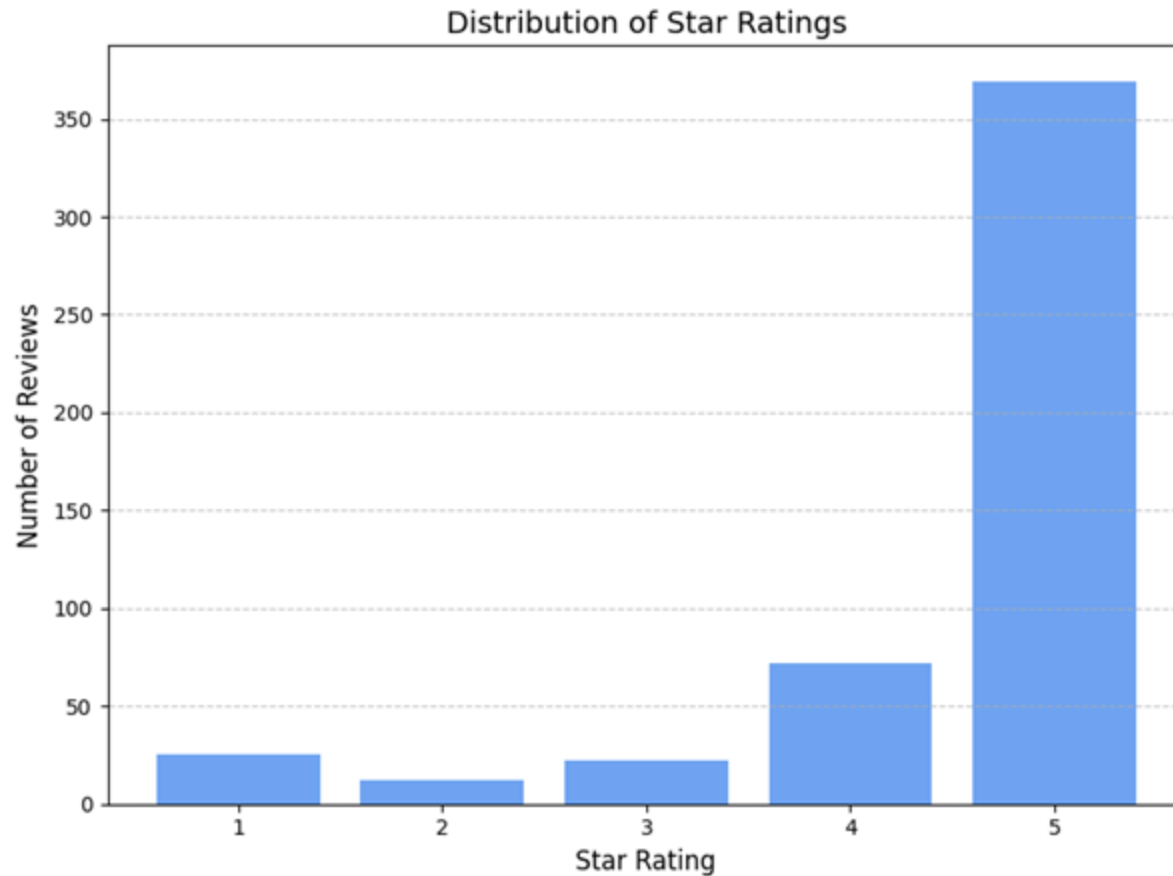
Some reviews may have incomplete labels, e.g.:

“Excellent machine. Fair price and guaranteed quality.” - **Positive Aspects:** [“Price & worth”]

Where is “Coffee Quality”?



# Experiments - Labels Distribution



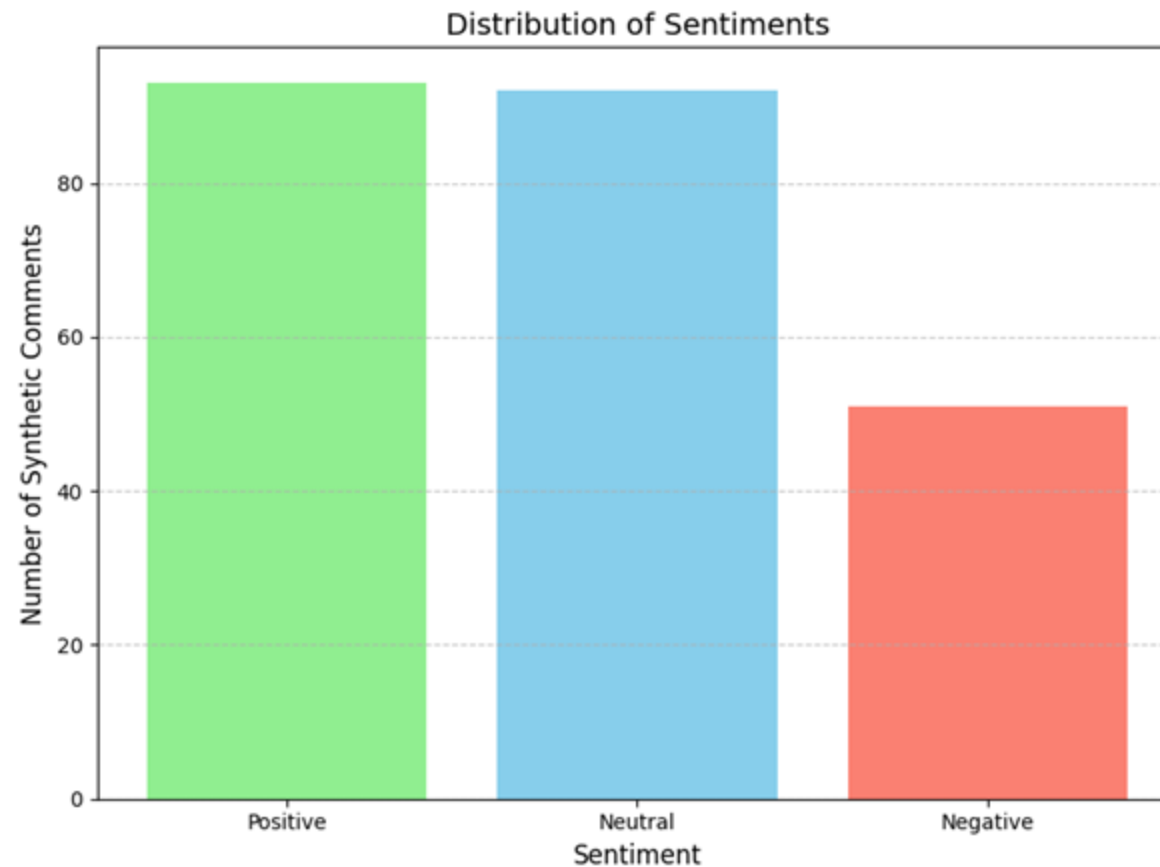
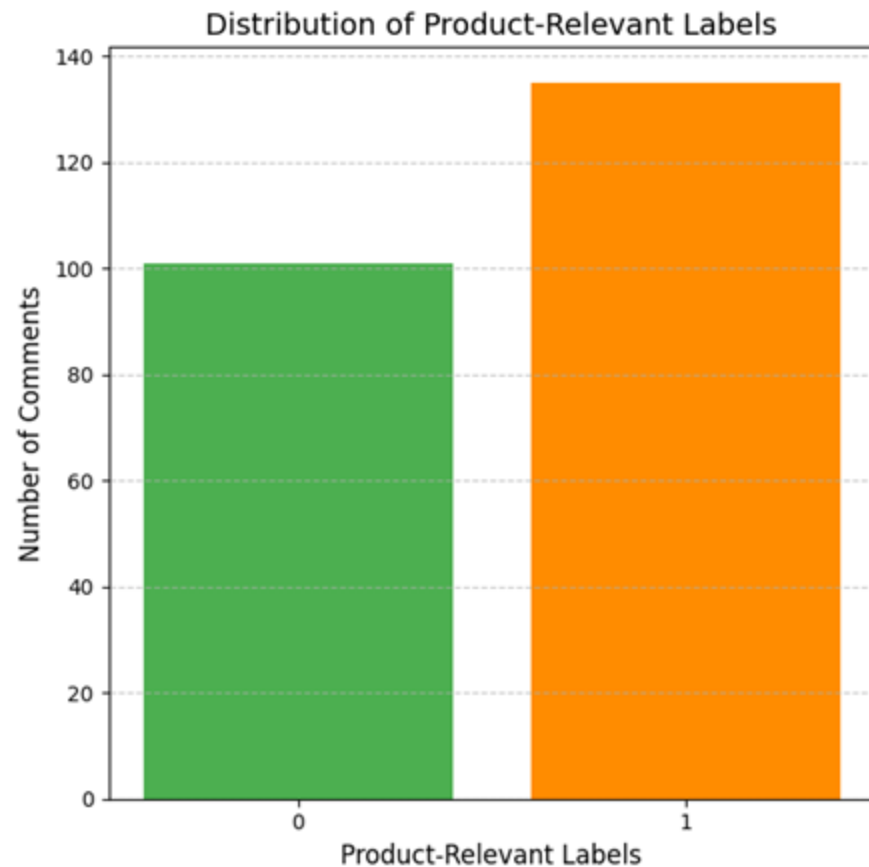
Heavily skewed toward  
**higher ratings!**



# Experiments - Labels Distribution



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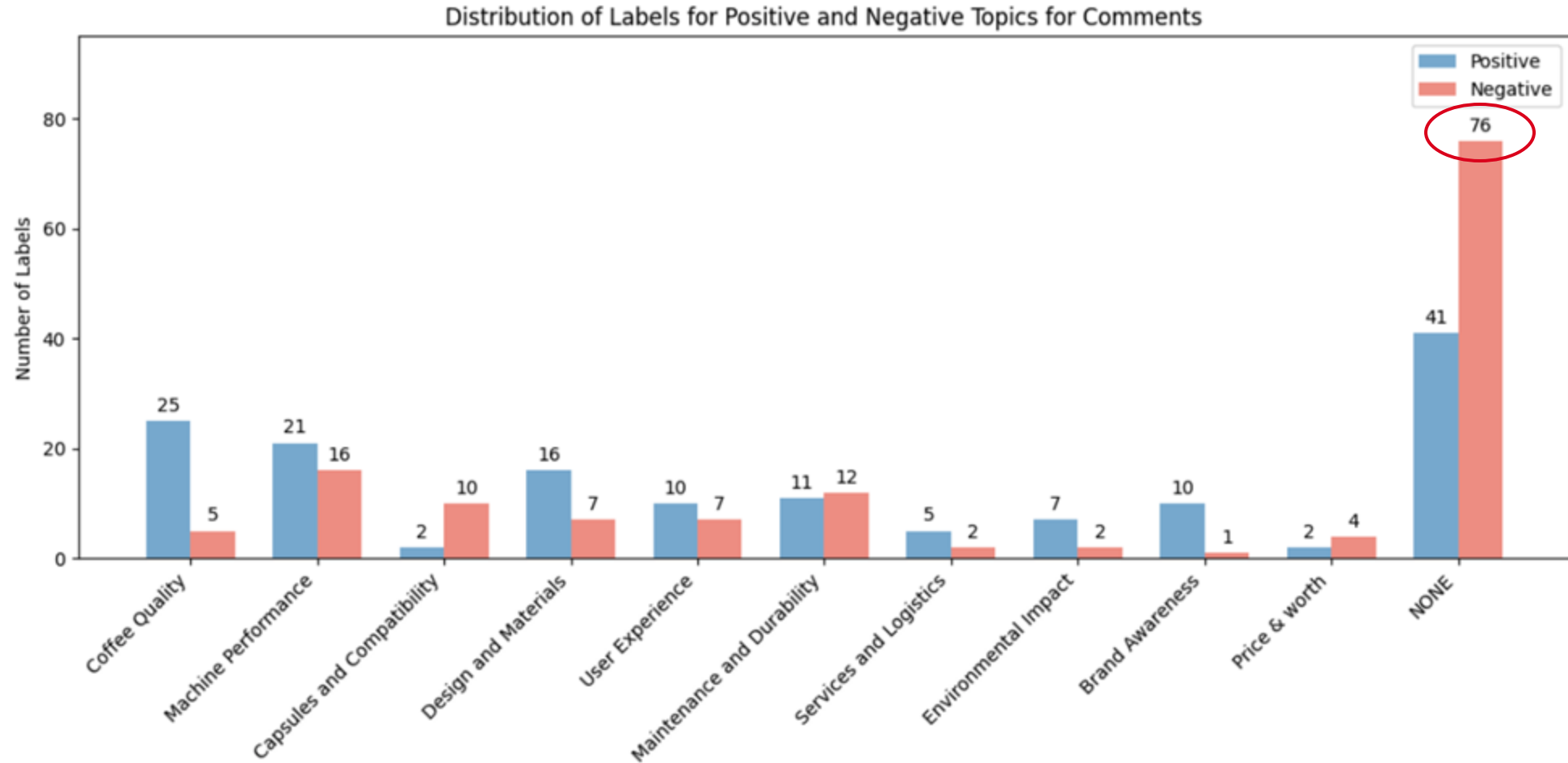
**Much more balanced!**



# Experiments - Labels Distribution



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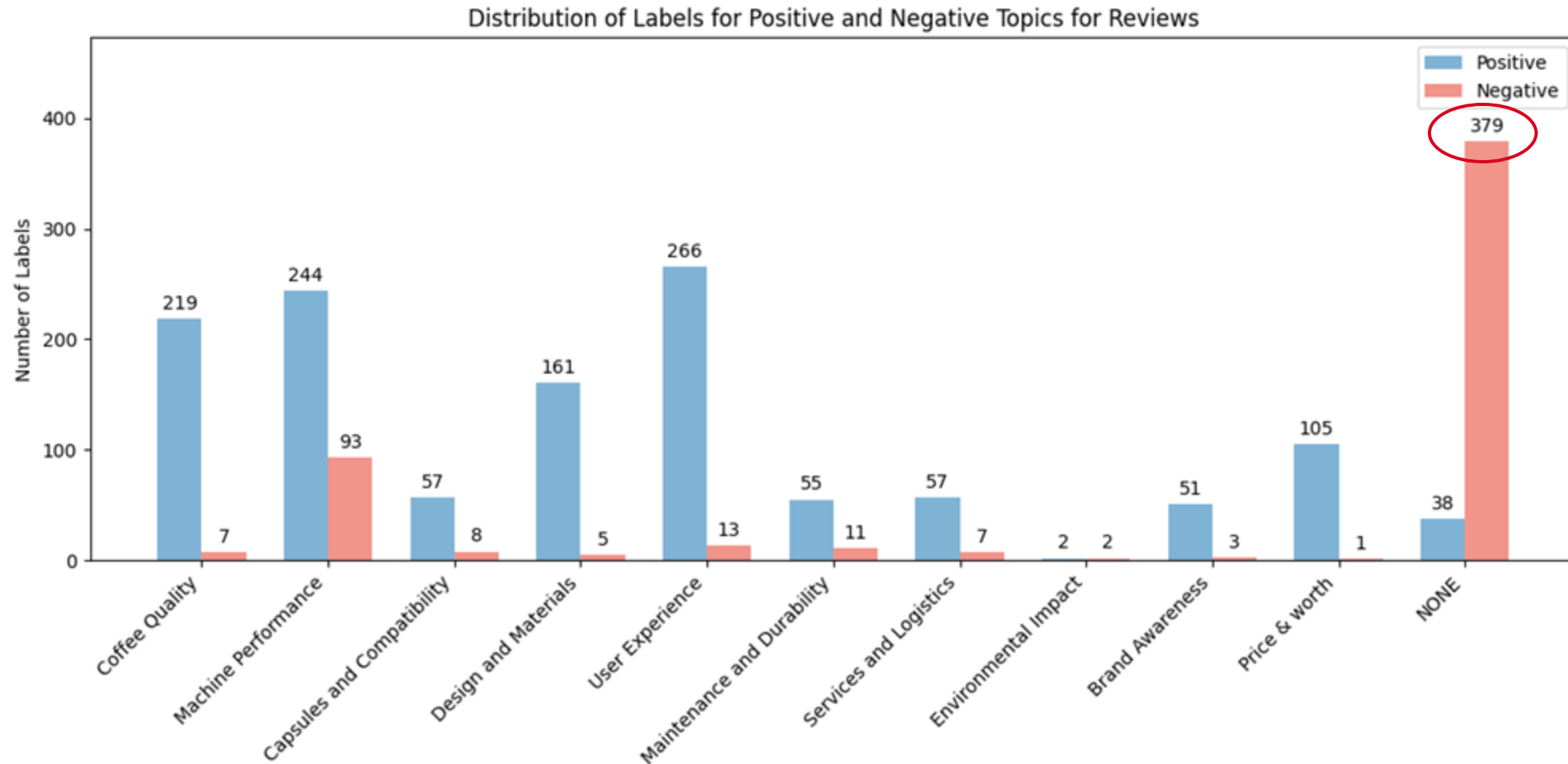




# Experiments - Labels Distribution



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# Experiments - Tasks



## 1. Product Relevant-Comment Classification

## 3. Sentiment Classification

- Positive
- Negative
- Neutral

## 1. Multi-topic Sentiment Classification

- Positive Topics
- Negative Topics

## 3. Star Rating Prediction:







# Experiments - Product Relevant-Comment Classification



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- **Data:** 236 synthetic comments
- **Batch-size:** 15 comments

Model	Acc.	Pre.	Rec.	F1	Time (s)
Gemma 0-shot	0.758	0.738	0.896	0.809	3.40
Gemma Few-shot	0.814	0.783	0.933	0.851	3.63
Llama 0-shot	0.763	0.737	0.911	0.815	<b>2.77</b>
Llama Few-shot	<b>0.826</b>	<b>0.794</b>	<b>0.941</b>	<b>0.861</b>	2.93
Mistral 0-shot	0.758	0.747	0.874	0.805	3.25
Mistral Few-shot	0.797	0.764	0.933	0.840	3.53

**Table 1: Metrics and Execution Times for Models for Product Relevant-Comment Classification**



# Experiments - Multi-topic Sentiment Classification

- **Data:** 500 labeled reviews + 236 synthetic comments
- **Batch-size:** 5 comment/review

Model	F1 (Neg.)	F1 (Pos.)	Prec. (Neg.)	Prec. (Pos.)	Rec. (Neg.)	Rec. (Pos.)	Time (s)
Gemma 0-shot	0.895	0.732	0.901	0.834	0.900	0.705	12.10
Gemma Few-shot	<b>0.899</b>	0.732	<b>0.905</b>	<b>0.844</b>	<b>0.904</b>	0.694	12.82
Llama 0-shot	0.880	<b>0.745</b>	0.901	0.795	0.879	0.718	<b>8.27</b>
Llama Few-shot	0.878	0.730	0.895	0.811	0.874	0.694	9.55
Mistral 0-shot	0.873	0.738	0.885	0.761	0.873	<b>0.735</b>	11.12
Mistral Few-shot	0.880	0.715	<b>0.905</b>	0.789	0.873	0.679	20.96

**Table 2: Weighted Metrics and Execution Times for Models for Multi-topic Sentiment Classification**



# Experiments - Sentiment Classification

- **Data:** 236 synthetic comments
- **Batch-size:** 20 (general purpose model) and 50 (specialized model)

Model	Acc.	Prec.	Rec.	F1	Time (s)
Gemma 0-shot	0.869	0.878	0.869	0.866	3.75
Gemma Few-shot	0.852	0.856	0.852	0.849	3.95
Llama 0-shot	0.818	0.818	0.818	0.815	2.76
Llama Few-shot	0.814	0.825	0.814	0.812	2.96
Mistral 0-shot	<b>0.877</b>	<b>0.880</b>	<b>0.877</b>	<b>0.876</b>	4.75
Mistral Few-shot	0.860	0.860	0.860	0.859	3.71
DB-sentimet	0.496	0.436	0.496	0.388	$6.52 \times 10^{-3}$
TR-sentimet	0.682	0.751	0.682	0.680	$6.77 \times 10^{-3}$
TRL-sentimet	0.831	0.837	0.831	0.829	$8.41 \times 10^{-3}$

Table 3: Weighted Metrics and Execution Times for Models for Sentiment Classification



# Experiments - Star Rating Prediction

- **Data:** 500 labeled reviews
- **Batch-size:** 20 (general purpose model) and 50 (specialized model)

Model	Acc.	Prec.	Rec.	F1	Off-1 Acc.	Time (s)
Gemma 0-shot	0.596	0.763	0.596	0.650	0.908	8.07
Gemma Few-shot	0.592	0.765	0.592	0.647	0.908	8.17
Llama 0-shot	0.682	0.764	0.682	0.713	0.948	5.73
Llama Few-shot	0.682	<b>0.777</b>	0.682	0.715	0.942	5.92
Mistral 0-shot	0.498	0.741	0.498	0.567	0.912	6.12
Mistral Few-shot	0.434	0.732	0.434	0.510	0.902	6.45
BBM-rating	<b>0.692</b>	0.757	<b>0.692</b>	<b>0.718</b>	<b>0.955</b>	0.158
MLA-rating	0.552	0.706	0.552	0.606	0.845	<b><math>10.45 \times 10^{-3}</math></b>

Table 4: Weighted Metrics, Accuracy, Off-by-One Accuracy, and Execution Times for Models for Star Rating Classification



# Conclusion

We can conclude by saying that:

- LLMs are able to identify **relevant product comments**, with an accuracy of up to **82.6%**.
- LLMs are able to extract **product aspects** from reviews and comments and **assign sentiment** to them, with an F1 score of up to **89.9%** for **negative** aspects and **74.5%** for **positive** aspects.
- LLMs are able to **assign sentiment** to comments and **rating stars** to reviews, with an accuracy of up to **87.7%** and **69.2% (95,5 off-by-one)** respectively.



# Conclusion



In conclusion we chose these models:

- **Gemma 2 few-shot:** for **Product Relevant-Comment Classification** and **Multi-topic Sentiment Classification**.
- **Twitter RoBERTa latest:** for **Sentiment Classification**.
- **BERT base multilingual:** for **Star Rating Prediction**.



The background is a dark blue gradient with diagonal white and light blue lines. On the left, a woman with curly hair is drinking from a white cup and holding a smartphone. On the right, a man is smiling. At the top right, there is a cup of coffee surrounded by coffee beans. At the bottom left, a pair of hands holds red coffee cherries.

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**Thank you**

**Alessio Gioè - Catalano Vincenzo - Tommaso Mazzarini**