



Architecting Azure Cloud Pipeline to Improve Product Information

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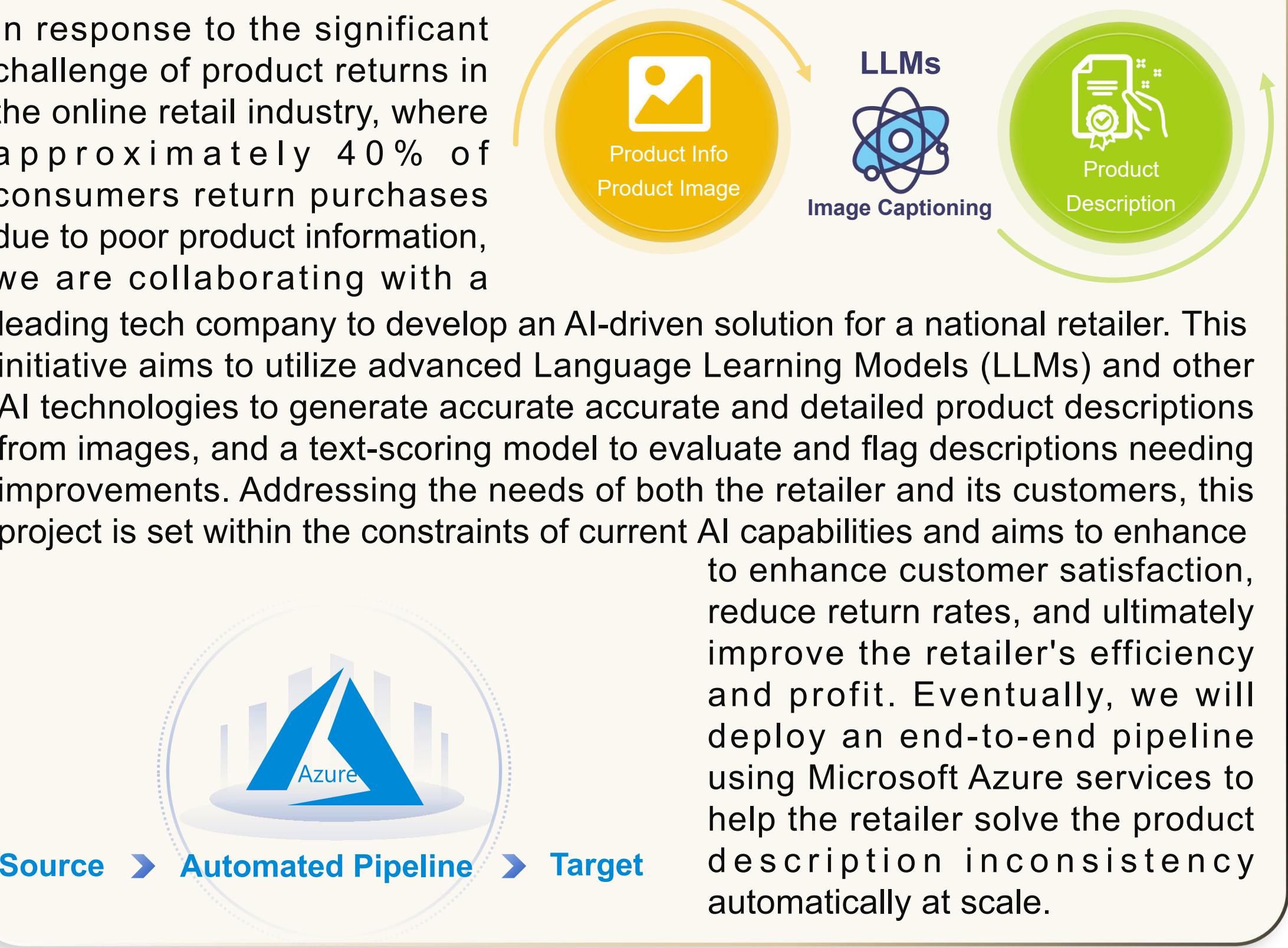
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THE TEAM

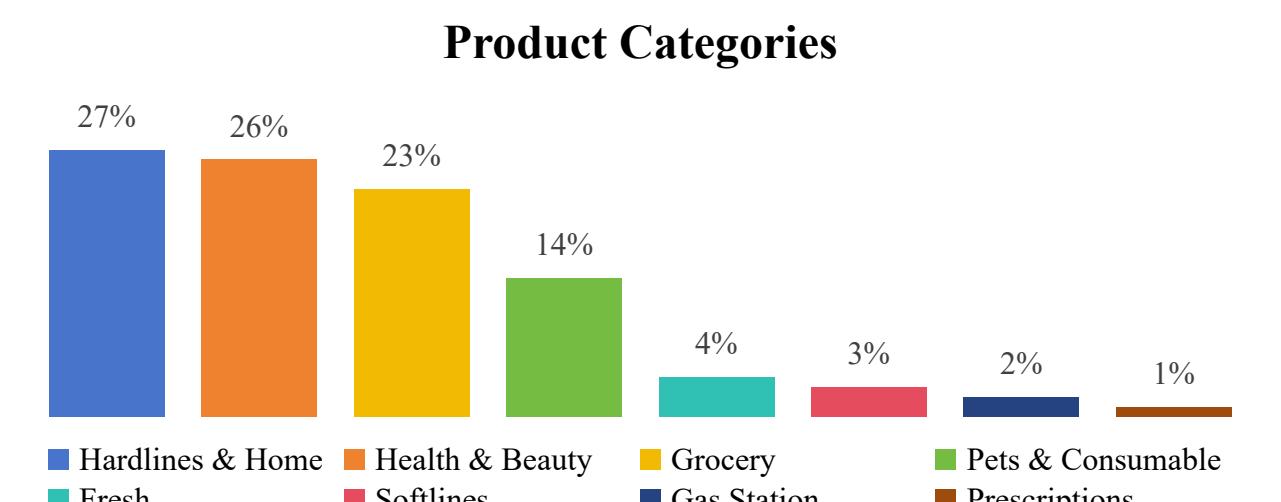


BUSINESS PROBLEM FRAMING



DATA

The dataset is provided by a major grocery store in the U.S. It comprises 309,826 unique products spanning diverse categories and contain attributes such as product names, descriptions, images(URL), and image angles.

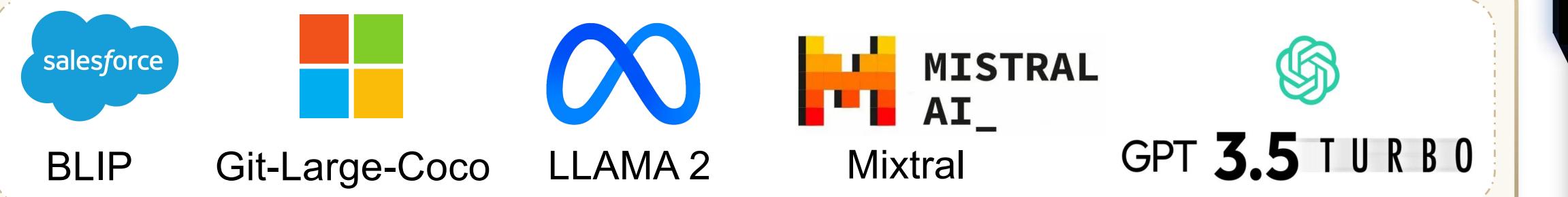


ANALYTICS PROBLEM FRAMING

Our project uses cutting-edge AI for automating online retail product descriptions, focusing on two tasks:

1. Image-to-text: To capture information from product images
2. Text-to-text: To refine auto-generated product description

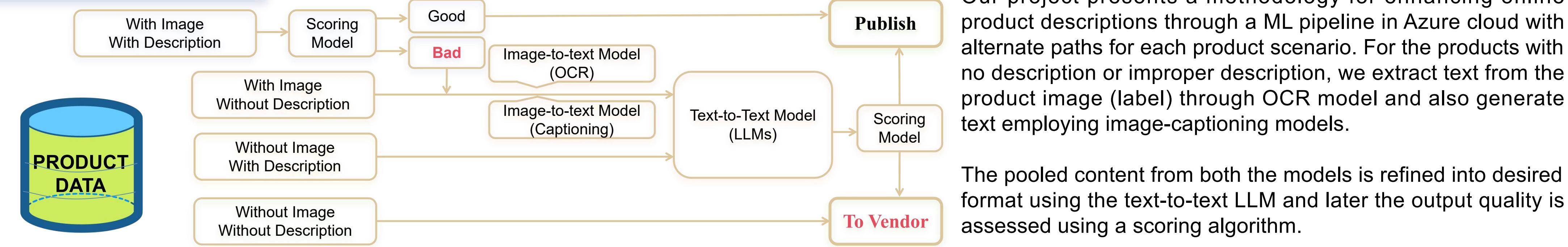
Based on practical trials with trending open-sourced models on Huggingface, we're confident in AI's capability for this task.



The generated text will be measured by a scoring model that focuses on 4 rubrics:

Readability, Relevance, Descriptive Language, Grammar

METHODOLOGY

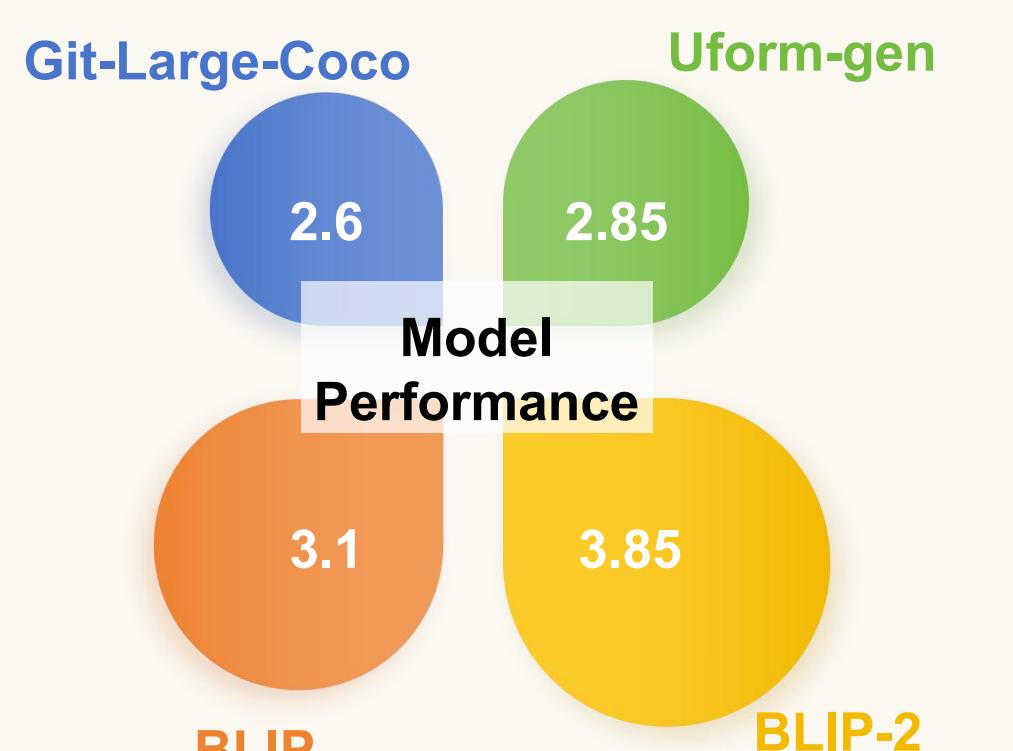


Our project presents a methodology for enhancing online product descriptions through a ML pipeline in Azure cloud with alternate paths for each product scenario. For the products with no description or improper description, we extract text from the product image (label) through OCR model and also generate text employing image-captioning models.

The pooled content from both the models is refined into desired format using the text-to-text LLM and later the output quality is assessed using a scoring algorithm.

MODEL BUILDING

Evaluating Image-to-Text Models:

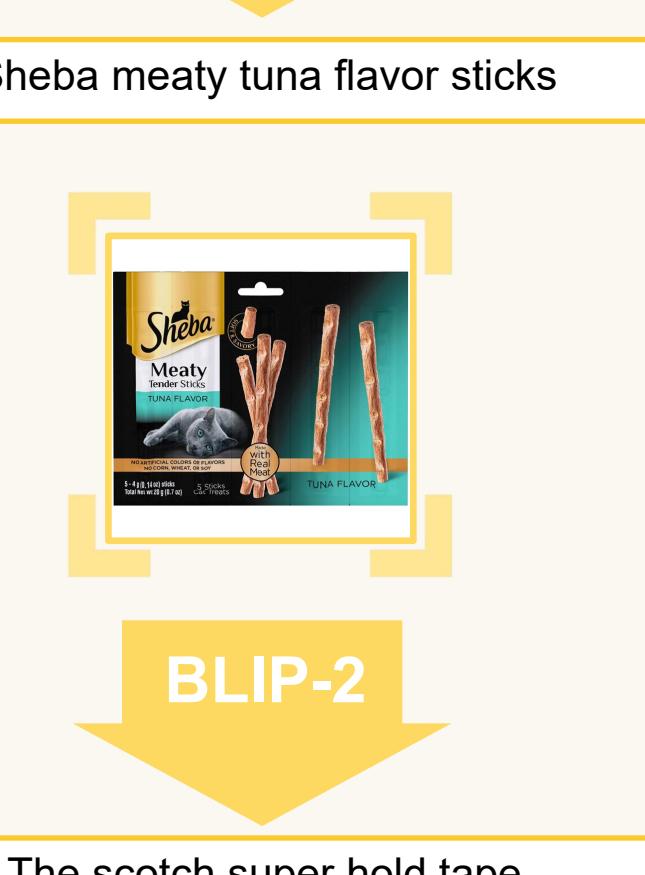


1. Sample Selection: 80 diverse product images across 8 categories.
2. Model Testing: Human evaluators rate text outputs from different open-source models on a 1-5 scale (1 = irrelevant, 5 = highly accurate).
3. Final Choice: Select the model with the highest average score for implementation.

Image Captioning



BLIP-2



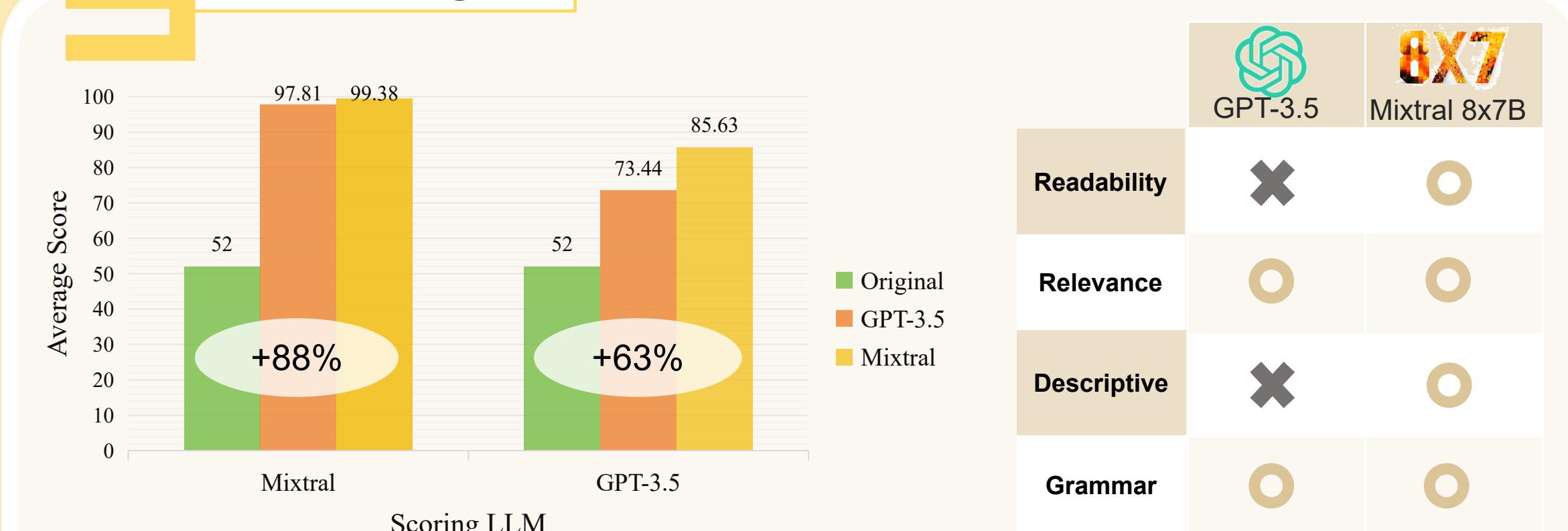
BLIP-2

LLM Generation

Scotch Super-Hold Tape

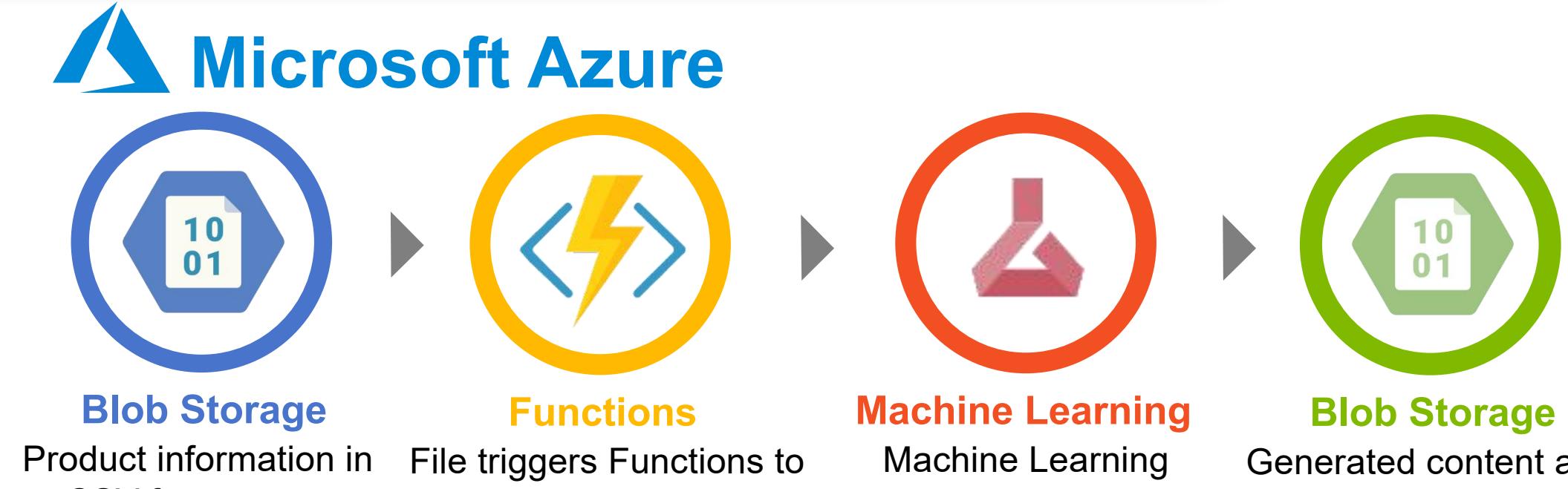
Experience superior adhesion with Scotch Super-Hold Tape, perfect for important jobs that require a strong, lasting hold. With 50% more adhesive than our standard transparent tape, this tape provides an exceptional bond, concealing confidential...

Scoring



We utilized LLMs to generate product descriptions and to score the results. Compared to the vendor-provided product information, our solution can increase the average quality score by more than 63% regardless of which LLM is used.

DEPLOYMENT & LIFE CYCLE MANAGEMENT



Product information in CSV format gets uploaded online

File triggers Functions to feed data into Machine Learning for action

Machine Learning generates product descriptions and scores

Generated content and scores are saved in CSV file

To deploy our solution, we developed an Azure pipeline that automatically processes product description creation and scoring. Architected with cloud services, the pipeline provides scalability, reliability, and cost-effectiveness. After deployment, we can seamlessly update our models without interrupting the service. Leveraging features such as model versioning, rolling updates, and A/B testing, we can iterate rapidly, adapt to user needs, and maximize business agility and competitiveness.



ACKNOWLEDGEMENTS

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