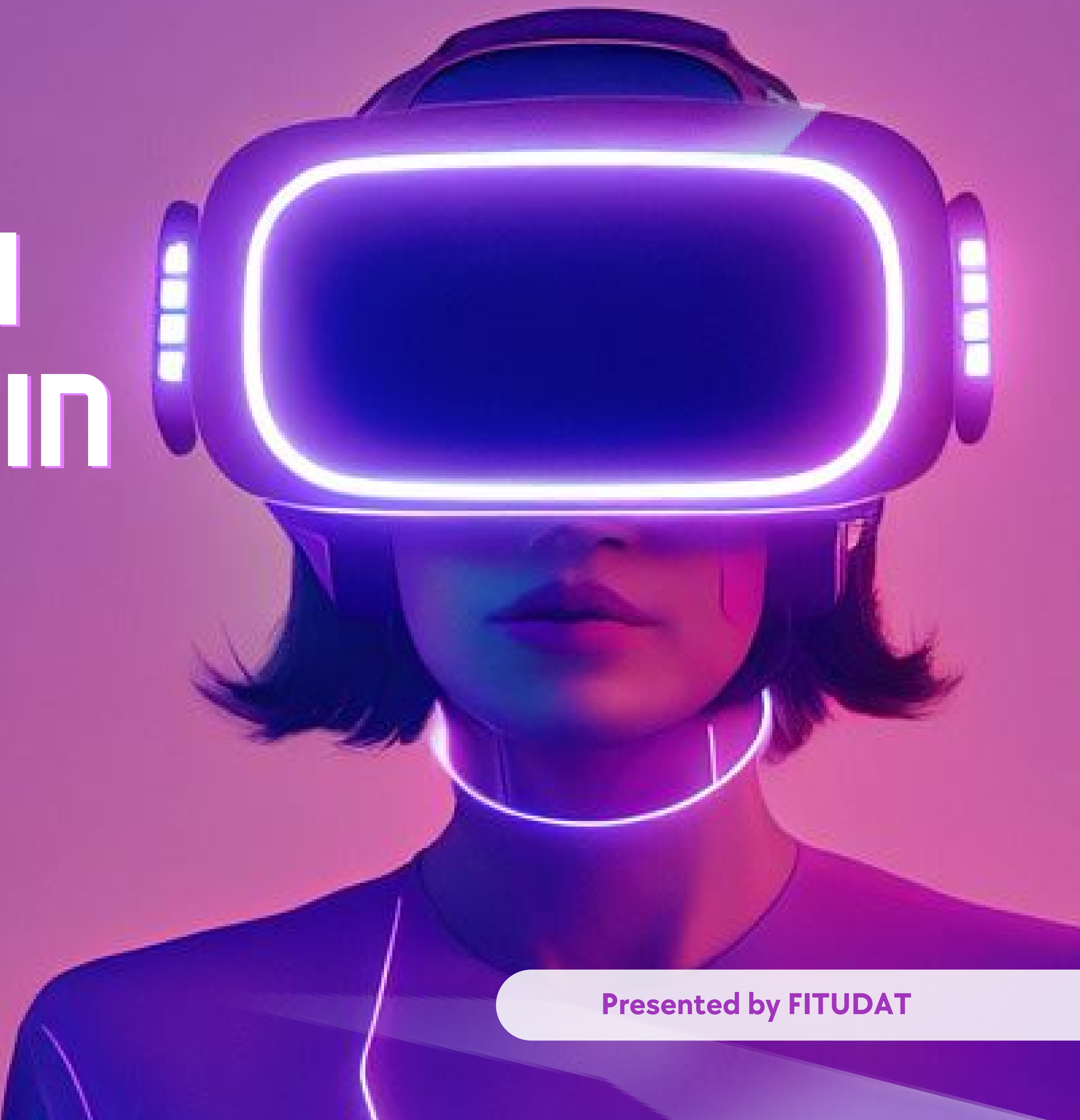
FITUDAT - AI APPLICATION IN SHOPPING

Let's start!



Presented by FITUDAT

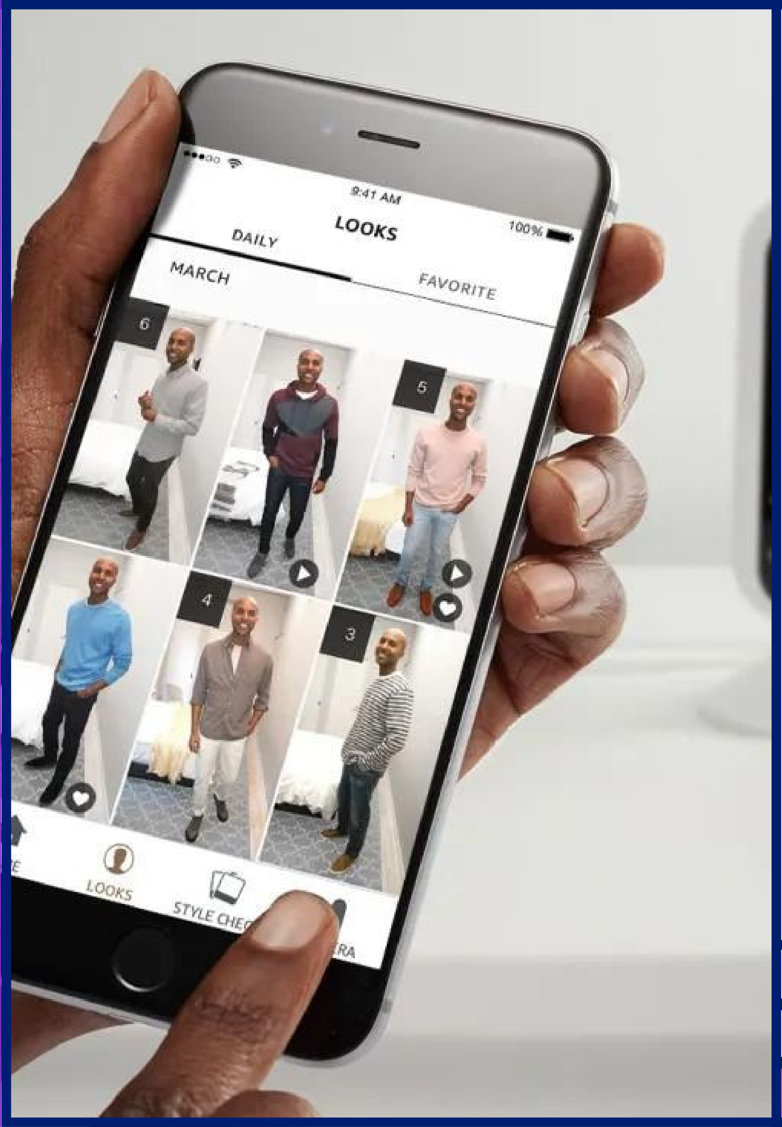
AGENDA

WELCOME!

Finding well-fitting clothes is a common challenge in today's overwhelming shopping landscape. Our innovative AI application, Fitudat, addresses this issue by seamlessly suggesting complementary items as customers browse the website, simplifying the shopping experience.

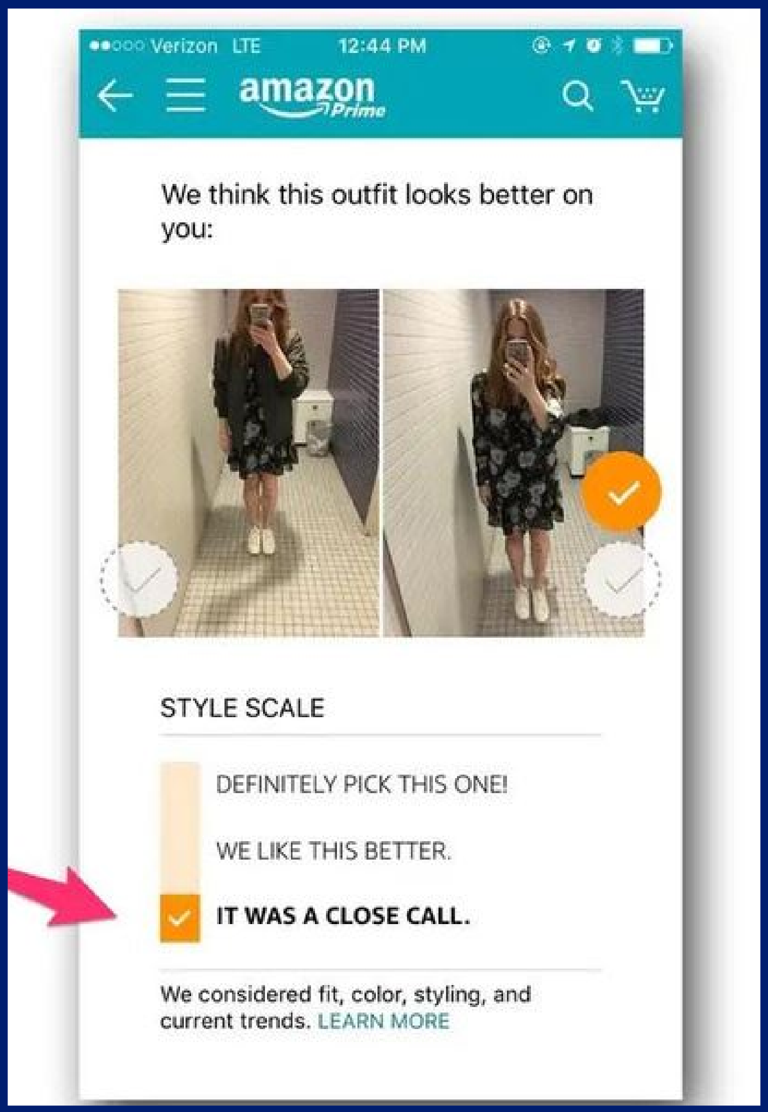
Notable competitors

Amazon Echo Look

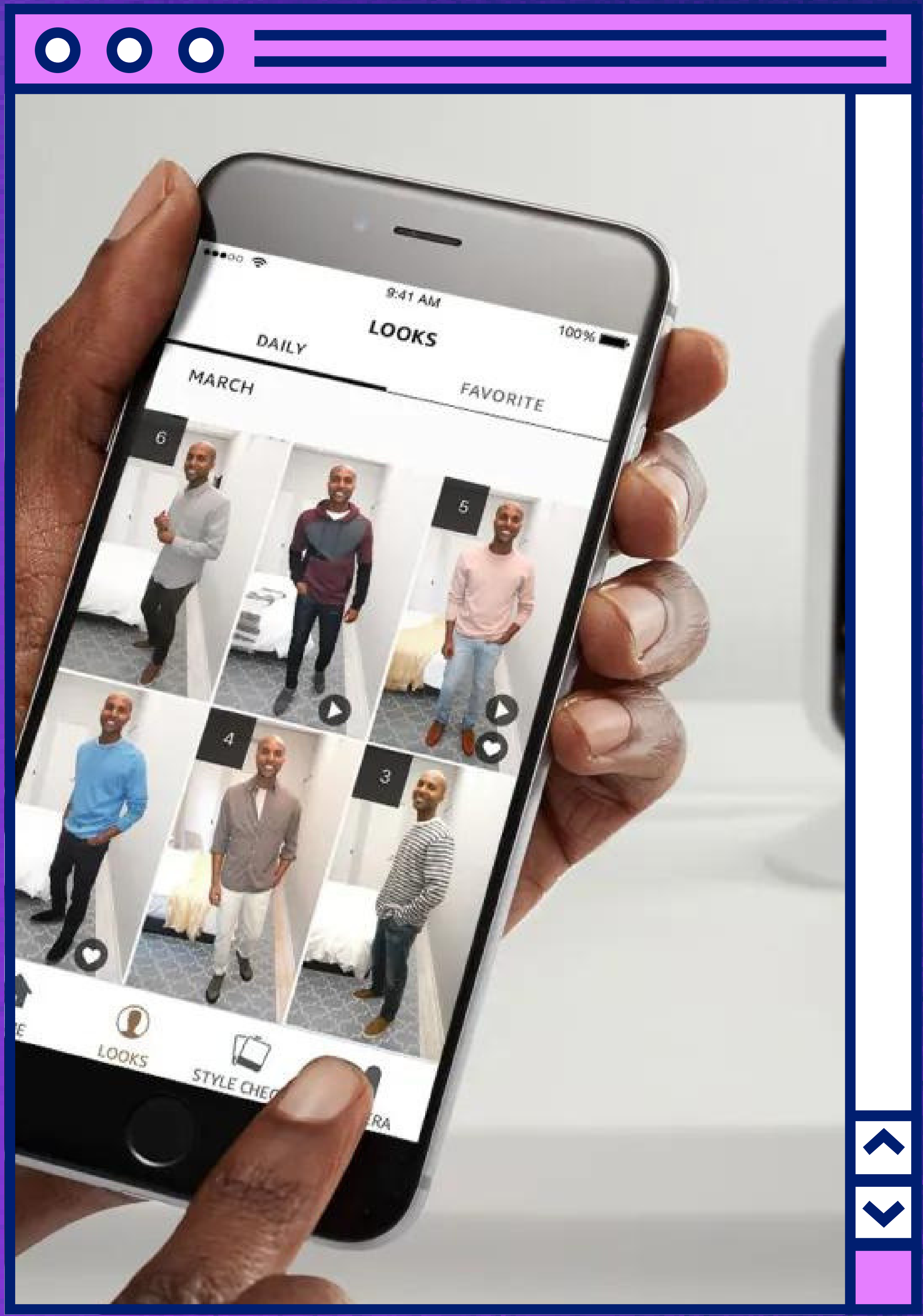


StyleSnap by Amazon

Outfit Compare by Amazon



Amazon Echo Look



- Aid in capturing images of their clothing
- Recommendation feature selecting between two outfits
- Lack of an in-depth and personalized recommendation system tailored to individual styles and preferences

=> Limiting its capacity to offer comprehensive and curated suggestions

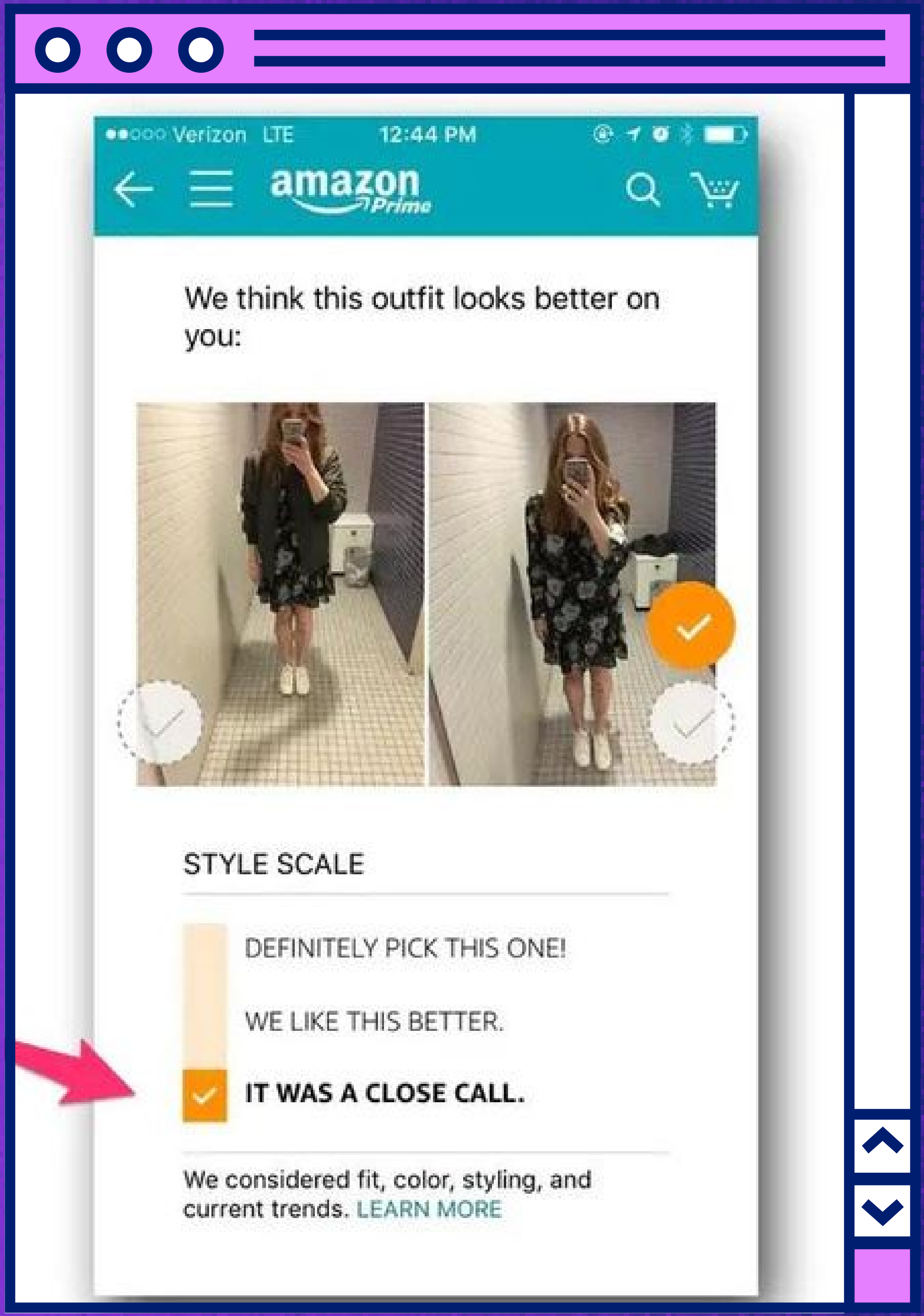
StyleSnap by Amazon

- Suggest similar items available on Amazon

- Recommend identical or closely matching items rather than focusing on suggesting complementary clothing items

=> Restrict the ability to provide diverse and well-coordinated suggestions to enhance an outfit with complementary accessories or additional garments

Outfit Compare by Amazon



- Compare between two uploaded outfits of the customer
- Lack of a comprehensive variety of styles
- Delay in obtaining results, typically ranging from one to five minutes

=> Generate recommendations less pertinent to users with diverse or distinctive fashion inclinations

FUTURE TECHNOLOGY

Our vision

Our solution revolutionizes outfit coordination and style curation with cutting-edge technology, prioritizing complementary clothing suggestions to offer instant, tailored recommendations and elevate the personalized fashion experience.

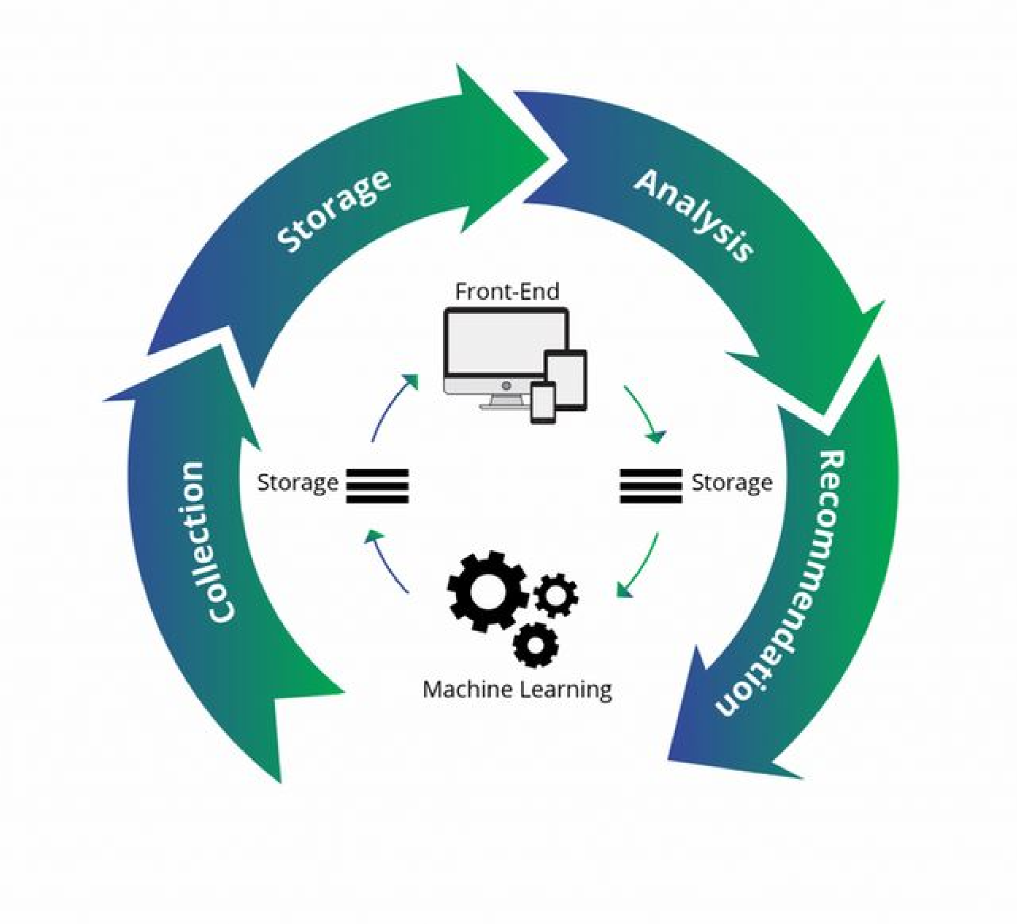
FITUDAT'S AI-POWERED SOLUTION

1. AUTOMATED RECOMMENDATION SYSTEM
2. CONTENT-BASED FILTERING MODEL
3. ITERATIVE LEARNING PROCESS
4. BUSINESS IMPACT AND AI UTILIZATION

Solution Overview

AUTOMATED RECOMMENDATION SYSTEM

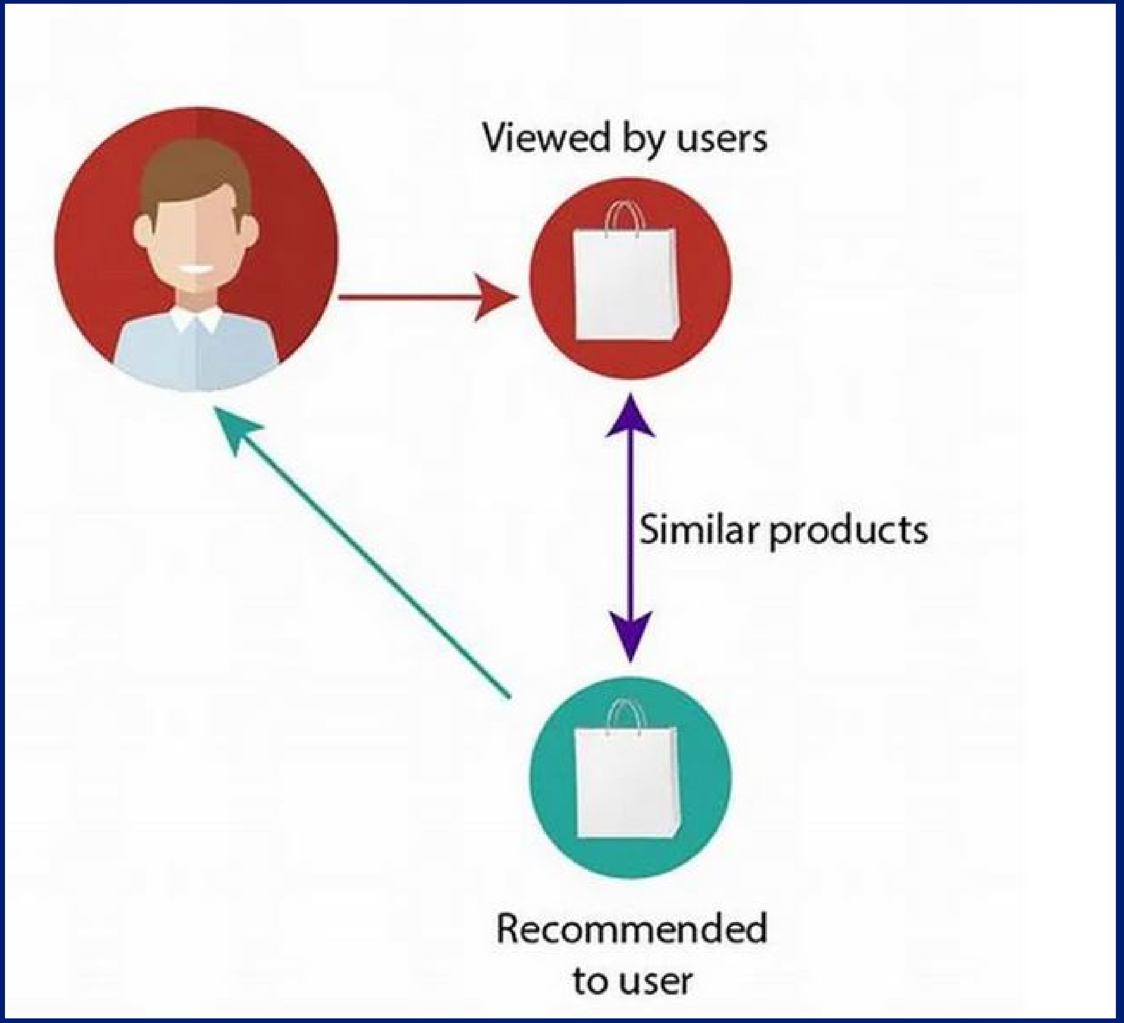
Our automated recommendation system leverages Machine Learning (ML) models to analyze product descriptions, discern patterns, and identify relationships among various products. By extracting essential features such as keywords, attributes, product types, and styles from product descriptions, our model determines similarities and relationships between items.



Solution Overview

CONTENT-BASED FILTERING MODEL

Utilizing a content-based filtering model, our system provides personalized recommendations based on user preferences and product attributes. This model analyzes product content, including descriptions, attributes, and user-generated tags, to identify relevant characteristics that match user preferences.



Solution Overview

ITERATIVE LEARNING PROCESS

- Our solution incorporates an iterative process of model training, evaluation, and optimization. This continuous learning loop adapts to changing preferences and evolving trends, enhancing recommendation accuracy over time.
- User interactions and feedback continuously refine the system's recommendations, aiming to improve customer satisfaction and engagement.

Solution Overview

BUSINESS IMPACT AND AI UTILIZATION

Our AI-powered solution aims to enhance the shopping experience by delivering personalized recommendations aligned with individual preferences. This not only improves customer satisfaction but also has the potential to boost conversion rates. Leveraging advanced AI algorithms enables businesses to offer a highly personalized shopping journey, fostering increased engagement and driving potential business growth.

Solution Overview

METHODOLOGIES

1. NLP TECHNIQUES
2. VECTORIZATION
3. SIMILARITY CALCULATION TECHNIQUES
4. USER PROFILING
5. RECOMMENDATION GENERATION PROCESS

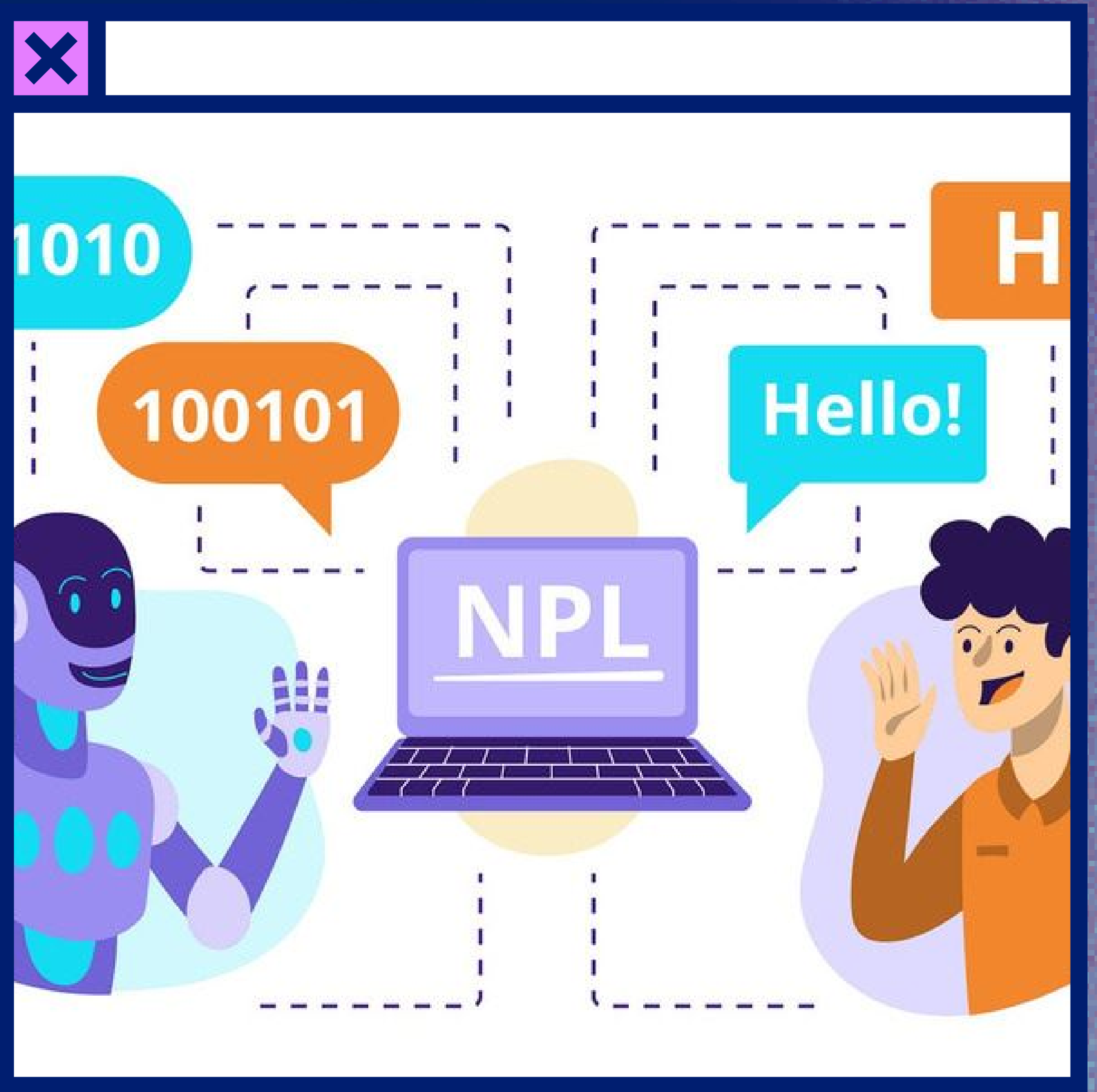
NLP TECHNIQUES

Feature Extraction

Natural Language Processing (NLP) techniques involves preprocessing text data, including tokenization, stemming, and potentially applying techniques like lemmatization to extract significant keywords and attributes from product descriptions.

NLP Libraries

NLP libraries like Natural Language Toolkit, spaCy, and Gensim offer specialized functionalities for text processing tasks like tokenization, stemming, lemmatization, and other necessary text preprocessing required for vectorization.



VECTORIZATION FOR REPRESENTATION

Conversion of extracted features into numerical representations, such as TF-IDF vectors or word embeddings, is employed to capture semantic relationships and characteristics within product descriptions.

TF-IDF and Word Embeddings

- TF-IDF (Term Frequency-Inverse Document Frequency): A numerical representation that captures the importance of words in a document relative to a corpus.
- Word Embeddings (e.g., Word2Vec, GloVe): Pre-trained word representations that capture semantic relationships between words.

SIMILARITY CALCULATION TECHNIQUES

Calculate the similarity between the user profiles and the product vectors using similarity metrics like cosine similarity or Euclidean distance. This measures the proximity between the user preferences and the product attributes.

Cosine Similarity and Euclidean Distance

- Cosine Similarity: A metric that measures the cosine of the angle between two vectors, often used to calculate similarity between vectors in recommendation systems.
- Euclidean Distance: A distance metric that calculates the straight-line distance between two vectors.

USER PROFILING

Creation of user profiles based on historical interactions and preferences results in vector representations that encapsulate user preferences for different product features or attributes.

RECOMMENDATION GENERATION PROCESS

The final stage involves recommendation generation, where the model selects items most similar to a user's preferences or current item of interest. Recommendations are ranked based on calculated similarity scores and presented to the user.

CORE FUNCTIONALITY

- Machine Learning from Product Descriptions
- Identify Important Features
- Comparison and Recommendation
- Integration of Content-Based Filtering
- User Interaction and Feedback
- User Profiles
- Continuous Training and Optimization
- Statistics and Reporting

MACHINE LEARNING FROM PRODUCT DESCRIPTIONS

- Develop a machine learning model capable of understanding and learning from detailed fashion product descriptions.

IDENTIFY IMPORTANT FEATURES

- Use machine learning techniques to identify crucial features from product descriptions, including details like descriptions, colors, styles, and materials.

COMPARISON AND RECOMMENDATION

- Compare the features of the currently viewed product with the product database.
- Recommend products with similar or related features based on the learned patterns and relationships.

INTEGRATION OF CONTENT-BASED FILTERING

- Compare the features of the currently viewed product with the product database.
- Recommend products with similar or related features based on the learned patterns and relationships.

USER INTERACTION AND FEEDBACK

- Collect user interactions and feedback to continuously improve the model. Adapt to changing preferences and enhance the quality of recommendations over time.

USER PROFILES

- Create and manage user profiles that store individual shopping history and preferences. This helps in tailoring recommendations based on the user's unique tastes.

CONTINUOUS TRAINING AND OPTIMIZATION

- Establish an iterative process for model training, evaluation, and optimization. This allows the system to adapt to evolving trends and user preferences, ensuring the recommendations remain relevant.

STATISTICS AND REPORTING

- Provide statistical insights and reports on system performance, accuracy of recommendations, and user feedback. This information helps in assessing the effectiveness of the recommendation engine and making further improvements.

PERFORMANCE METRICS

1. USER ENGAGEMENT
2. USER SATISFACTION

USER ENGAGEMENT METRICS

- **API Interactions**: Measure the frequency of user access to the clothing recommendation API.
  - **Tracking Method**: Utilize logging and tracking tools to record the number of API calls within specified time frames.
- **Interaction Duration**: Monitor the average time users spend engaging with recommended clothing items through the API.
  - **Measurement Approach**: Implement timestamp tracking to measure duration between API requests and user interaction periods.

USER SATISFACTION METRICS

- **Planned Surveys**: Gather feedback through periodic surveys, assessing user satisfaction and ease of use.
    - **Survey Distribution**: Schedule surveys at specific intervals via email.

- **Feedback Integration**: Enable users to provide ratings, reviews, and comments directly on recommended clothing items through the API.
    - **Integration Method**: Integrate a feedback feature within the API response for user input.

- **API Response Monitoring:** Ensure swift delivery of recommendations by monitoring and logging API response times.
    - **Measurement Process:** Track time from request initiation to response delivery for each user request.

TARGET AND EXPECTATION

- **API Interactions**: Aim for a **10%** monthly increase in user engagement **within the first three months** post-launch.
- **Interaction Duration**: Target an average interaction duration of at least **120 seconds** per session in the initial month to signify sustained user engagement.
- **Planned Survey**: Target a **15%** minimum survey response rate to gather comprehensive user feedback and assess satisfaction levels.
- **Feedback Integration**: Aim for an average rating of **4 out of 5** stars for recommended clothing items to validate their usefulness and relevance.
- **Response Time**: Maintain an API response time consistently under **1.5 seconds** per request for a seamless user experience.

TIMELINE AND ROADMAP

November 6 - December 17

Market and Dataset Researching (Nov 6 - Nov 10)

Product Ideation and Goal Definition (Nov 11 - Nov 19)

Researching & Developing the Product (Nov 20 - Dec 7)

Testing & Debugging the product (Dec 8 - Dec 15)

Participate in the competition (Dec 16 - Dec 17)

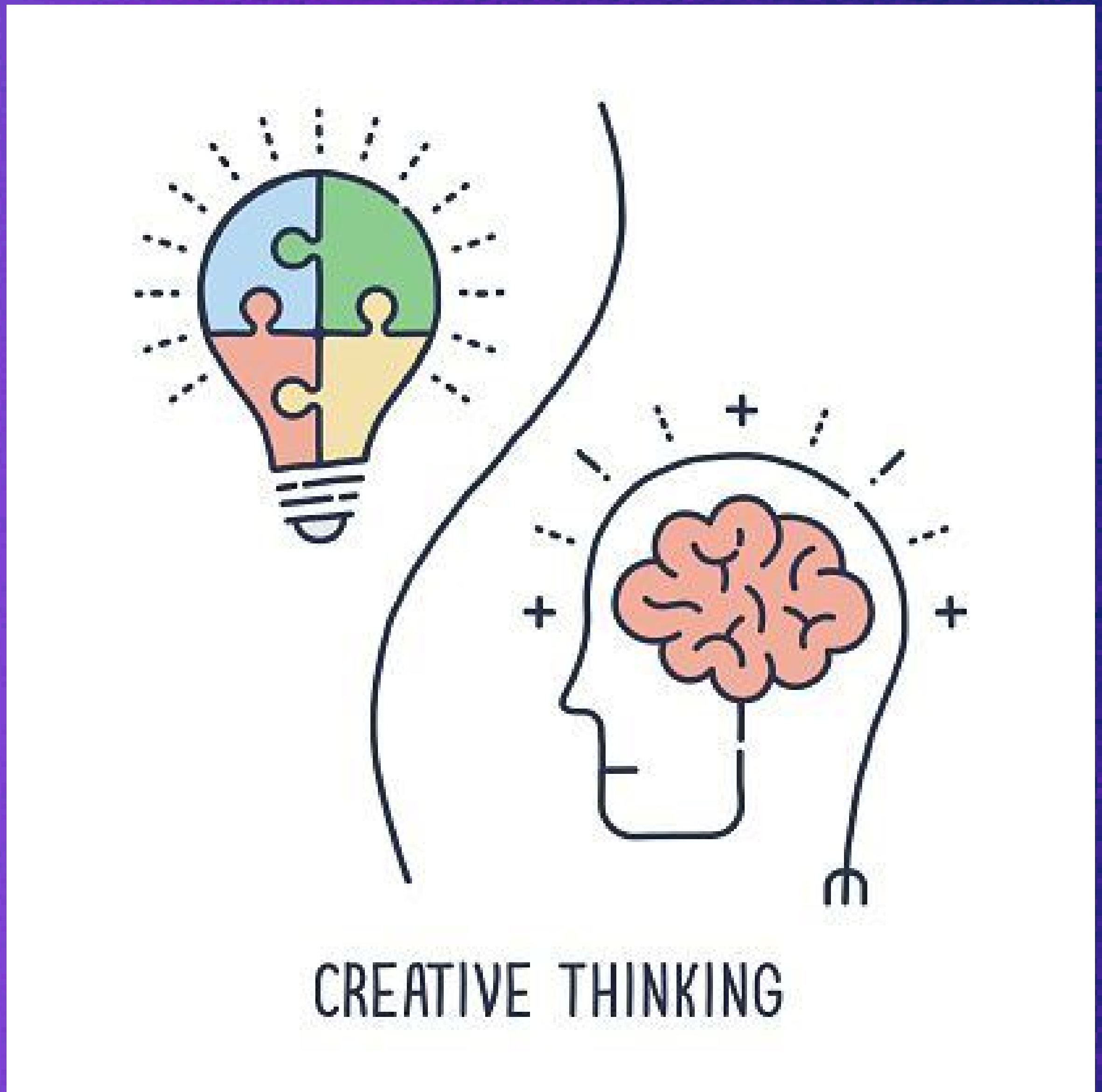
MARKET AND DATASET RESEARCHING

NOVEMBER 6 - NOVEMBER 10

- Conduct an in-depth exploration of market research within a 2-day timeframe.
- Explore and understand the competition's provided dataset within a 3-day timeframe.

PRODUCT IDEATION AND GOAL DEFINITION

NOVEMBER 11 - NOVEMBER 19



- Each team member actively contributes to researching and brainstorming ideas for the product and its objectives over a span of 4 days.
- We come together to participate in discussions aimed at proposing the most fitting concept within a single day.
- We delve into researching and discussing ideas for the detailed components of the product, streamlining its construction process over 4 days.

RESEARCHING & DEVELOPING THE PRODUCT

NOVEMBER 28 - DECEMBER 7

- Drawing upon the team's ideas and decisions, develop intricate components of the product over the course of 6 days.
- Generate pertinent data associated with the selected dataset for continuous product training, allocating 6 days to this task.
- Conduct routine testing and updates to promptly detect and rectify errors.
- Learn and receive feedback from mentos during workshops to enhance the product further (December 2 - December 3).
- Collaborate with personal insights and mentor guidance to elevate the product within a 4-day timeframe.

TESTING & DEBUGGING THE PRODUCT

December 8 - December 15

- Leverage mentor feedback to consistently improve the product within a 4-day timeframe.
- Testing and QA within a 4-day timeframe.

PARTICIPATE IN THE COMPETITION.

DECEMBER 16 - DECEMBER 17

- Acquire the complete dataset and investigate newly obtained data.
- Fine-tune the product to suit the newly acquired data.

LIMITATIONS AND FUTURE ENHANCEMENTS

LIMITATIONS

FUTURE ENHANCEMENTS

LIMITATIONS

- **Accuracy and Scoring Criteria:** Product accuracy for general users ranges from 75% to 90%, relying on overall trends for scoring.
- **Data Requirements:** High accuracy requires large datasets, impacting efficiency and development time.
- **Development Time:** Achieving perfection for large-scale deployment demands a significant time investment.
- **Cold Start Challenge:** The system faces challenges in generating accurate recommendations for new users or products lacking sufficient historical data, affecting initial accuracy.

FUTURE ENHANCEMENTS

- **Continuous Improvement**: Ongoing refinement leveraging new data and user feedback will enhance the product's accuracy and relevance.
- **Feature Expansion**: Focus on developing features catering not only to the general population but also ensuring suitability for diverse user segments.
- **Data Optimization**: Strengthen data cleaning processes to curate more relevant and useful data for the product's training and recommendation processes.

FUTURE ENHANCEMENTS

- **Adaptation to Trends**: Regular updates to keep the product aligned with the latest fashion trends and preferences.
- **Iterative Testing and Improvement**: Implement A/B testing and iterative improvements to assess changes in user engagement based on variations in recommendation algorithms or API responses.
- **Retailer Collaboration:** Collaborate with retailers to access comprehensive datasets, including detailed user actions, purchases, and preferences within their platforms, enriching the product's metrics and insights.

CONCLUSION

In summary, "Fitudat," our AI-driven clothing recommendation system, utilizes advanced machine learning for accurate outfit suggestions, ranging from 75% to 90% precision. More than just enhancing shopping, "Fitudat" aims to boost conversion rates, enhance user engagement, and ensure customer satisfaction. Positioned to redefine personalized fashion discovery in the evolving e-commerce landscape of 2023, "Fitudat" commits to revolutionizing how users engage with complementary clothing, promising unparalleled shopping experiences through continuous improvement and a user-centric approach.

THANK YOU!