Game Recommendation: A Story Driven Approach

The Story Today:

We believe that a user's decision to play a game is not a random process, but one prompted by **certain fixed and traceable drivers.** A good recommendation engine should not be one that overlooks these characteristic **but one that actively accounts for them**

Individual Propensity

People's urge to play a game is affected by several modelable and understandable human factors

Popularity

Key Rationale: people's propensity to play is closely related to **the hottest game on the street**

Social

Key Rationale: people play games that **their friends and social circles** plays

Content

Key Rationale: people play games similar to the kind of games **that they played before** (Generation & Genre)

Favorability

Key Rationale: people play games that **received credibility rating** and reviews from the community

Individual Propensity

Weighted Collaborative filtering based approach to assess game popularity

Popularity

Rationale	*Caveat*	*Procedure*
people's propensity to play is closely related to **the hottest game on the street**	The hottest game on the street should not be a single measure of popularity but a **weighted one by the *user similarity* but also an indicator of *user activity***	Employed collaborative filtering based methods whereby we evaluate the ***user similarity*** **based on *their level of activity on the games.*** The similarity **will then be multiplied with the user activity** to obtain the ranking of recommended games

Notes:

Level of activity (Addictive Index) = Number of active days a player spent in a game

Standardized addictive index = scaled addictive index where the most active player in each game is 1

Similarity calculation: absolute difference in standardized activity index between players

Recommendation per user: similarity vector multiplied by the unscaled addictive index of each user in a game, summed across all users.

Weighted Collaborative filtering based approach to assess game popularity

Popularity

	User
User	***Similarity Matrix Calculated Through CF***

	Game
User	***Unscaled Addictive Matrix***

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Trial adjustment: users on trial period are weighted by 0.5 (we are concerned with potential profits)

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Individual Propensity

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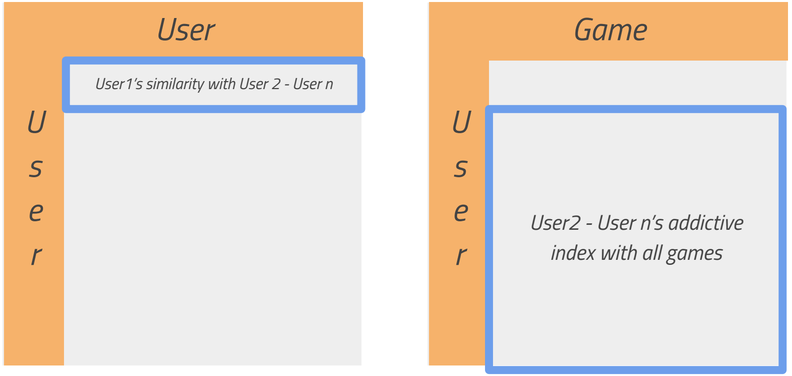

Procedure

We then weighted each User's addictive index by their respective weight in terms of similarity with user 1.

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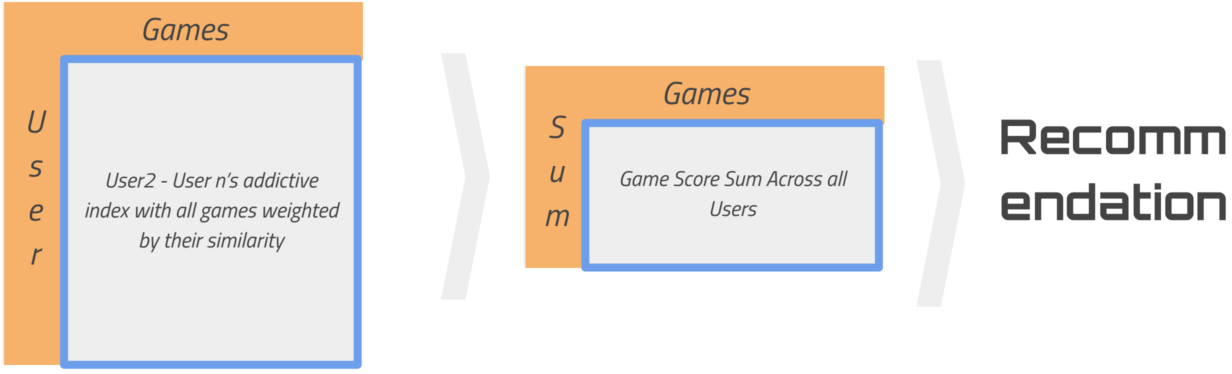

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Demographic approximation of the network effect in game consumption

Social

Rationale	*Caveat*	*Procedure*
people play games that **their friends and social circles** plays	We don't have information on the actual social circle of an individual - however, using relevant **demographic information (age & country)** to create a social network proxy	Extracted user pairwise differences based on their demographics information to generate **a social proximity metric**. From there we weighted the games using the addictive matrix with said proximity metric to produce the recommendation

Notes:

Demographic differences: 1. Whether or not two users are in the same country, 2. The difference in age of the two users. The final matrix is a weighted sum of the 2.

Addictive matrix: this refers to the scaled addictive index that was constructed earlier

Individual Propensity

Demographic approximation of the network effect in game consumption

Popularity

	User
User	***Proximity/ Social Network Matrix***

	Game
User	***Scaled Addictive Matrix***

Notes:

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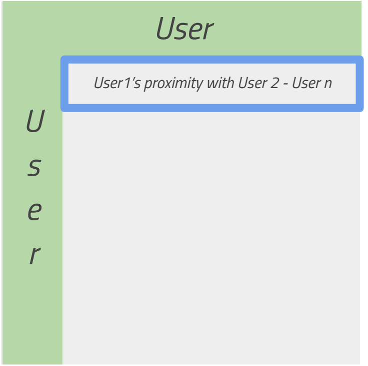
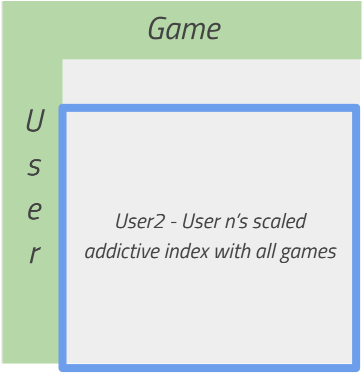
Demographic approximation of the network effect in game consumption

Popularity





Procedure

Similar to previously, We then weighted each User's scaled additive index by their respective weight in terms of proximity with user 1.

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Addictive matrix: this refers to the scaled addictive index that was constructed earlier

Individual Propensity

Demographic approximation of the network effect in game consumption

Popularity

Games

User

User2 - User n's scaled addictive index with all games weighted by their proximity

Games

Sum

Game Score Sum Across all Users

Recommendation

Notes:

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Addictive matrix: this refers to the scaled addictive index that was constructed earlier

Weighted content based metric to reflect user specific defined preference

Content

Rationale	*Caveat*	*Procedure*
people play games similar to the kind of games **that they played before** (Generation & Genre)	Similarity of games differs in degree and ultimately impacts user propensities in various ways as well. For this analysis, we mainly focused on **genre, subgenre (genre category), generations (franchise)**	Using the three metrics indicated, we constructed a gamewise similarity matrix, where we calculated how similarity is one game to another. We then referenced the games that a user played in the past to generate **the most similar game in line with the user's history**

Notes:

Game Similarity rating: We assigned the score of 1 for genre, 2 for subgenre and 3 for generations

Individual Propensity

Weighted content based metric to reflect user specific defined preference

Content

	Game
User	***The Games A User played***

	Game
Game	***Game pairwise Similarity matrix***

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Individual Propensity

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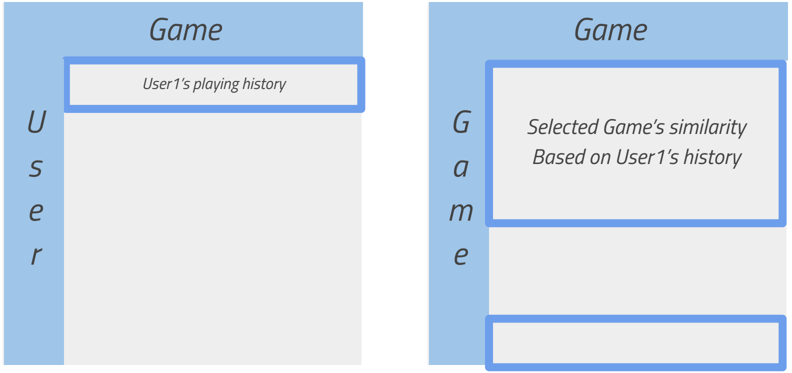


Procedure

We investigate User 1's playing history to the obtain the pairwise game similarity with those games that User 1 has already played

Notes:

Game Similarity rating: We assigned the score of 1 for genre, 2 for subgenre and 3 for generations

Individual Propensity

Weighted content based metric to reflect user specific defined preference

Content

Games

Game

Selected Game's similarity Based on User1's history

Games

Sum

Game Score Sum Across all Games played by User 1, while setting those played to 0

Recommendation

Notes:

Game Similarity rating: We assigned the score of 1 for genre, 2 for subgenre and 3 for generations

Individual Propensity

External data sources to generate overall sentiment and happiness score around a game

Favorability

Rationale	*Caveat*	*Procedure*
people play games that **received credibility rating** and reviews from the community	We need to ensure that the recommendation we pushed forward are GOOD games, so people **don't get disappointed and even turn away from our platform**	Performed sentiment analysis based on twitter tweets [1] about the games along with online ratings [2] to generate a **game review metric that can be used in guiding our final recommendation.**

Notes

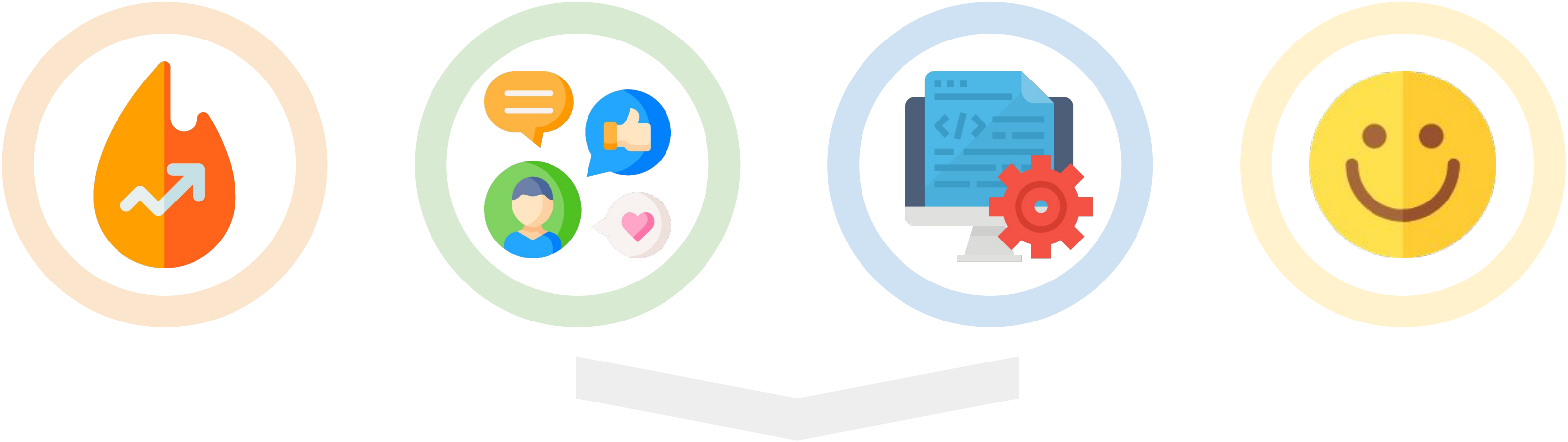
1. Compound score calculates the sum of all the lexicon ratings which have been normalized between -1 and +1
2. Pulled critic and user ratings from https://www.vgchartz.com/.

The Story Then:

The individualized metrics can each be seen as a **mini recommendation engine on its own.** However to achieve a truly customer centric product, it is necessary for the final model to be an encompassing one that **accounts for each metric, performs considerably well** and handles **edge cases with grace.**

Aggregate Results

Employ time variant majority voting to generate initial set of recommendation for each user



Procedure

Rank recommendations by total times appeared in the **Top 10 of all 4 recommendation engines**. If there were to be a tie, the tie will be broken by the **recency of the game release.** From there the top 10 ranked recommendations will be our initial final recommendations

Model Evaluation

Assess model performance and the business Impact of our prediction

We held out approximately the last 5 months of the total dataset to use for our testing. In particular we examined our prediction for the 10 most active users and validated our accuracy.

Q1: For users that continued to use the platform and played **NEW GAMES**, how many of which **were recommended by us**?	**Q2:** For users that continued to use the platform and **played NEW GAMES**, how many of which **were not recommended by us**	**Q3:** How many games **were recommended by us**, that the **user didn't play**
Answer: 4.2 Games	Answer: 18 Games	Answer: 5.8 Games
Implications: Through our recommendation we could have migrated these users earlier and facilitated more purchase	**Implications:** These portion of added revenue will not be cannibalized as the engine will not be hurdle for user's exploration	**Implications:** We believe this segment is the biggest potential revenue source. These are likely the games that the players have not explored but may be interested in

Grounded In Reality

Accounting for the edge cases whereby based on the amount of data available

Returning User

Key Characteristic: *Available Historical Data to make inference from and thereby generate accurate prediction*

For these kind of users our algorithm could perform quite well

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New User

Key Characteristic: *No Available Historical Data to make inference from and thereby would have to depend on demographics*

Our algorithm in this case would make **prior guesses based on where this user is from and his/her age in combination with the generally popular games**

The Story Untold:

Scaling this technology further, implies that we must challenge a very fundamental assumption that we made. We aim to create an engine that **grows and iterates through time!**

Next Steps

Weighting update upon more observation to generate weight adjustments and better customize to users

So Far

Up until now, we are presuming users treats each of these category of recommendations **with equal amount of weights**

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In Reality

Each and every user likely have vastly different and **heterogenous preference over each of these metrics.**

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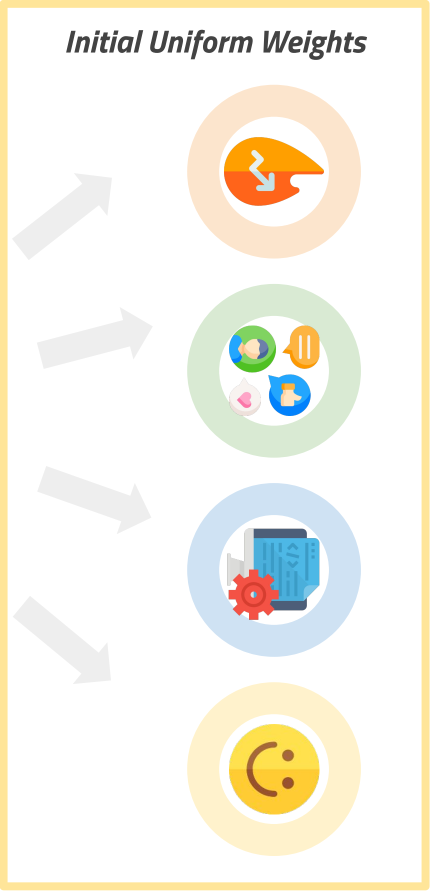

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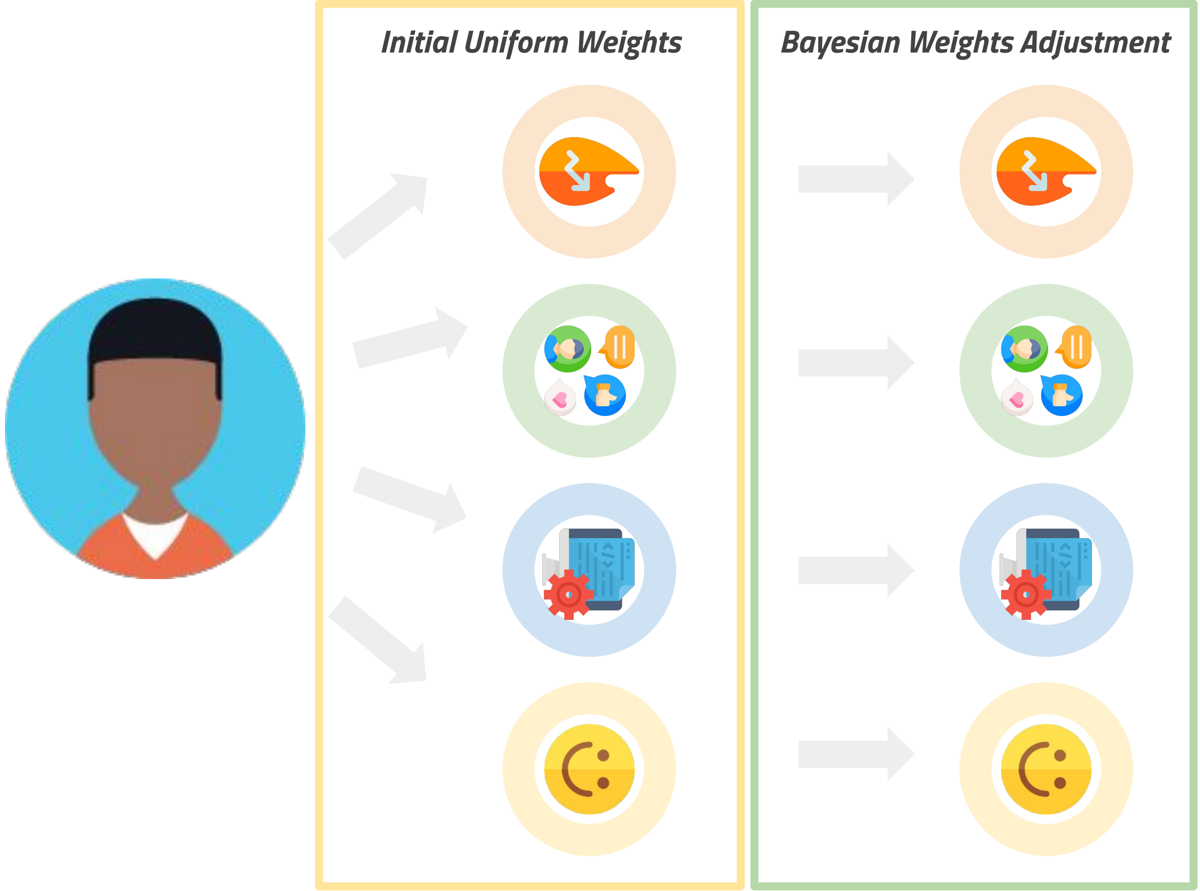

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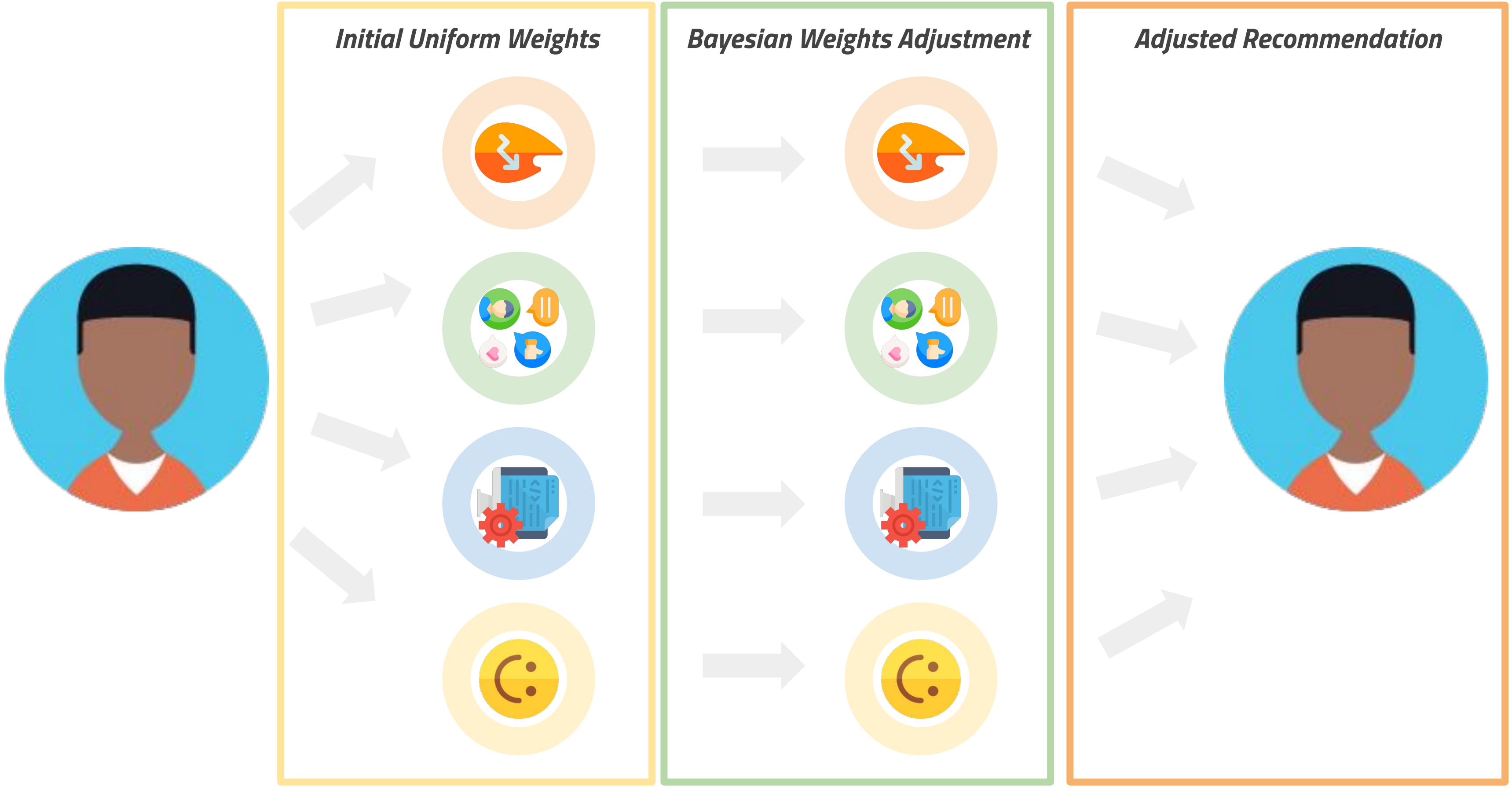

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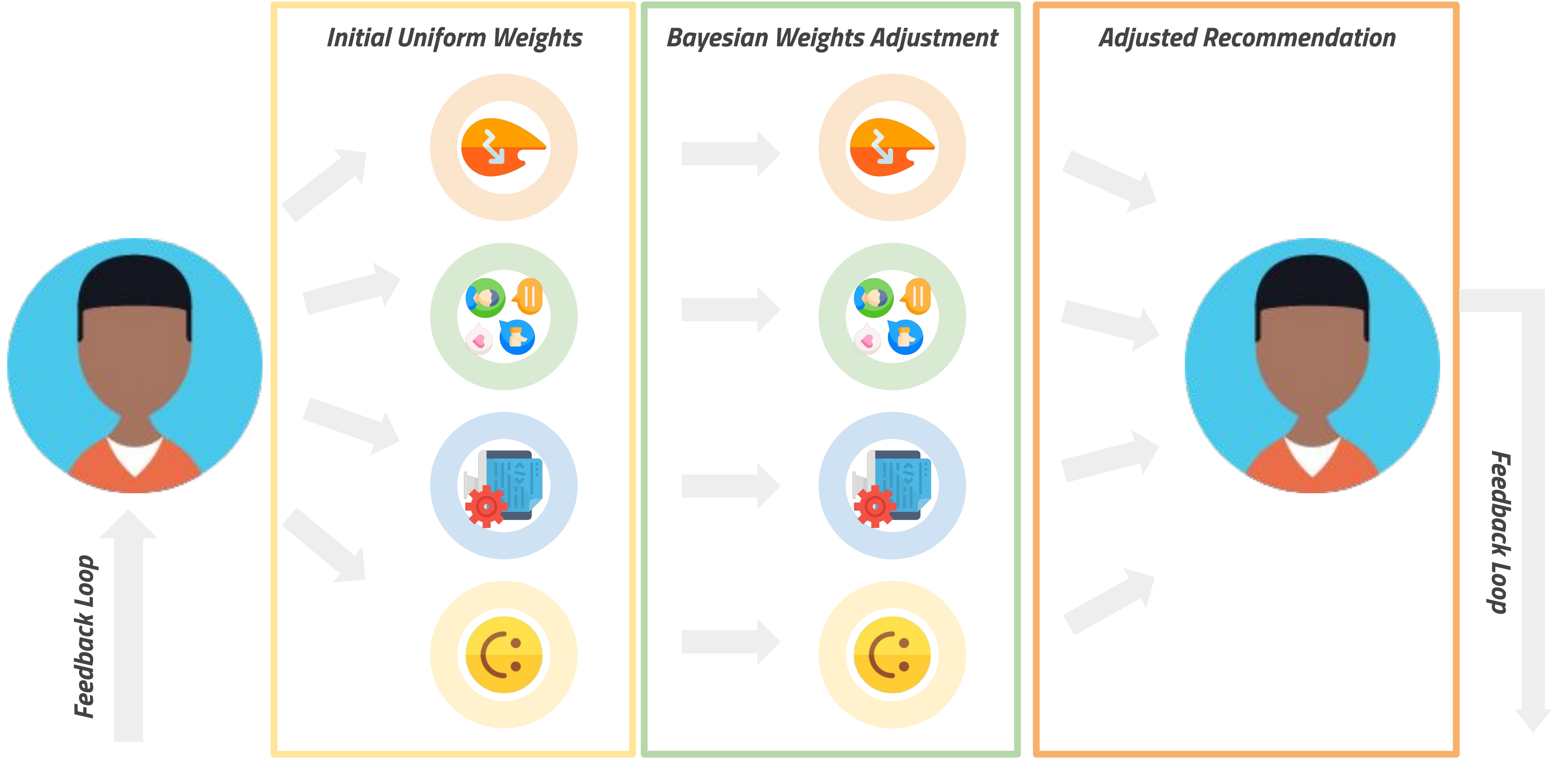

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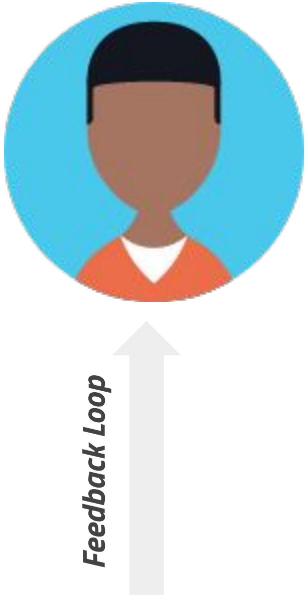
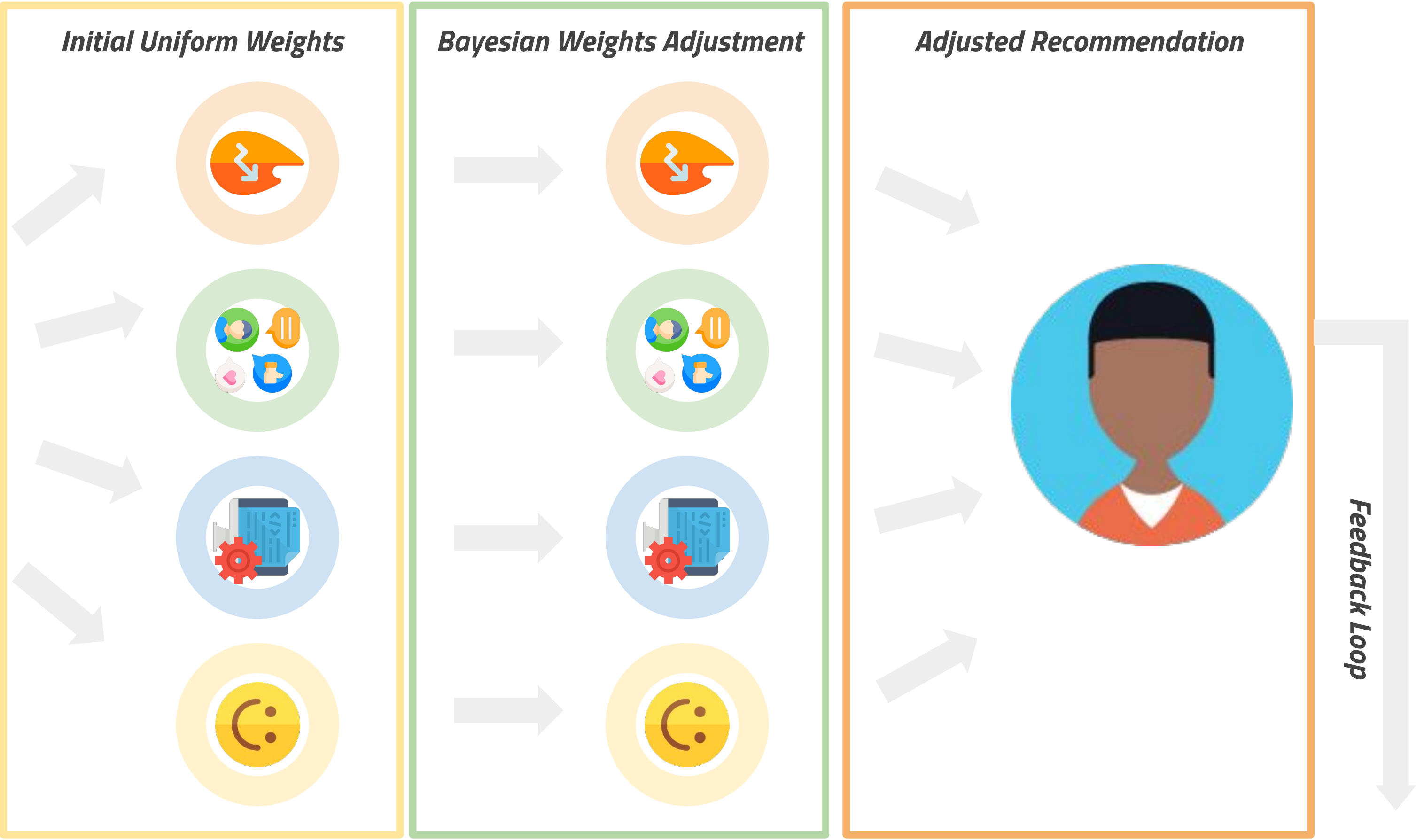
Envision

Our engine is never static but one that will grow with time





Thank you! Any Questions?