



Making the World *Playful*

How AI automation increases the content relevancy in Candy Crush Saga

King

- Founded in 2003
- 200+ published games, most known – Candy Crush Saga, Candy Crush Soda Saga and Farm Heroes Saga
- Part of Activision-Blizzard since February 2016
- Part of Microsoft since October 2023
- ~ 2000 employees currently

- **Candy Crush Saga** (released 2012)
 - free-to-play tile-matching game
 - >17 000 levels
 - in Europe, teams spread across Stockholm, Barcelona, London, Berlin, Malmö (check out new job openings!)



Candy
Crush Saga



Candy Crush
Soda Saga



Farm Heroes
Saga



Making the World *Playful*

Candy Crush Saga



- Tile-matching game “Match 3”
- Players match candies in combinations of three or more to progress through levels, each with unique challenges and objectives
- Over 17 000 levels, constantly adding new levels to the game

Why we want to integrate AI to Candy Crush and other games?

To enhance experience of players and make the game more relevant for everyone:



Understanding of player preference



Displaying more relevant content



Increase player's engagement, retention and social interactions

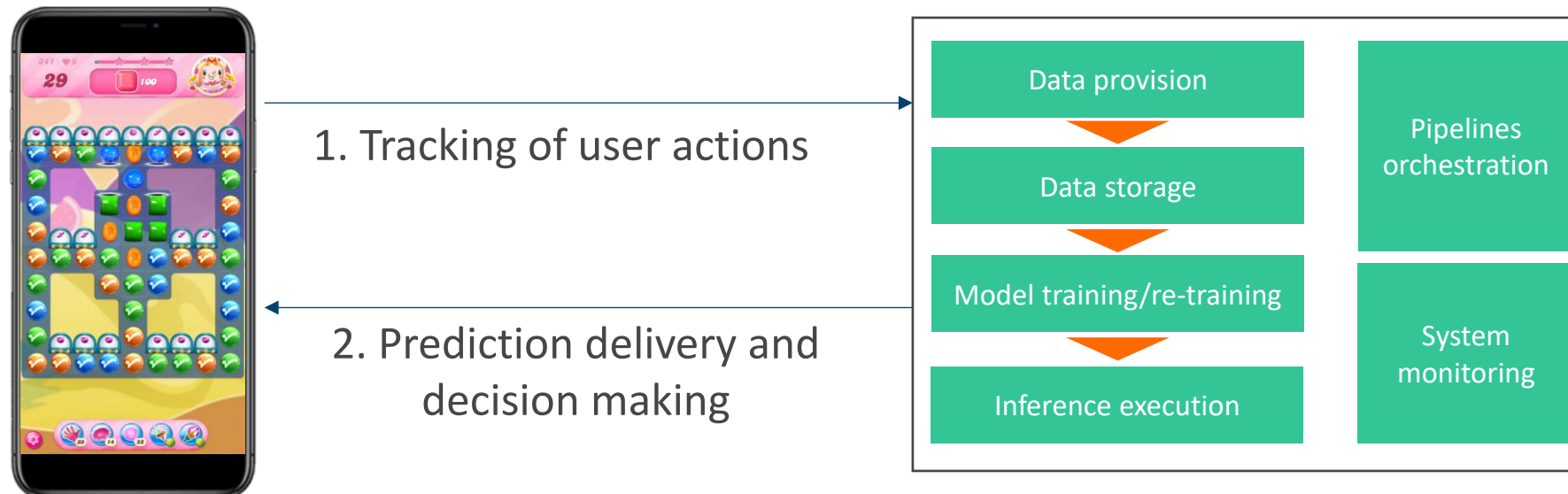
Problem statement – integration of AI solutions is challenging

1. Getting the right data via **tracking**

- There is high data maturity for analytical puposes, but not always for AI/ML pipelines (data granularity, consistency, contextual information)

2. Choosing the right way of **integration**

- Game client built 12 years ago without thinking too much about AI automation (one has to take existing codebase to take into account)



1. Getting the right data via tracking
2. Choosing the right way of integration
3. Use-case example
4. Main takeaways

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Getting the right data via tracking

- **Challenges**

- high data maturity for analytical purposes, but not always for AI/ML pipelines (data granularity, consistency – format for different game features, contextual information)
- data availability – option for both batch and low-latency processing
- client-server data delivery delay
- risk of data loss (e.g. due to poor connection of the client)

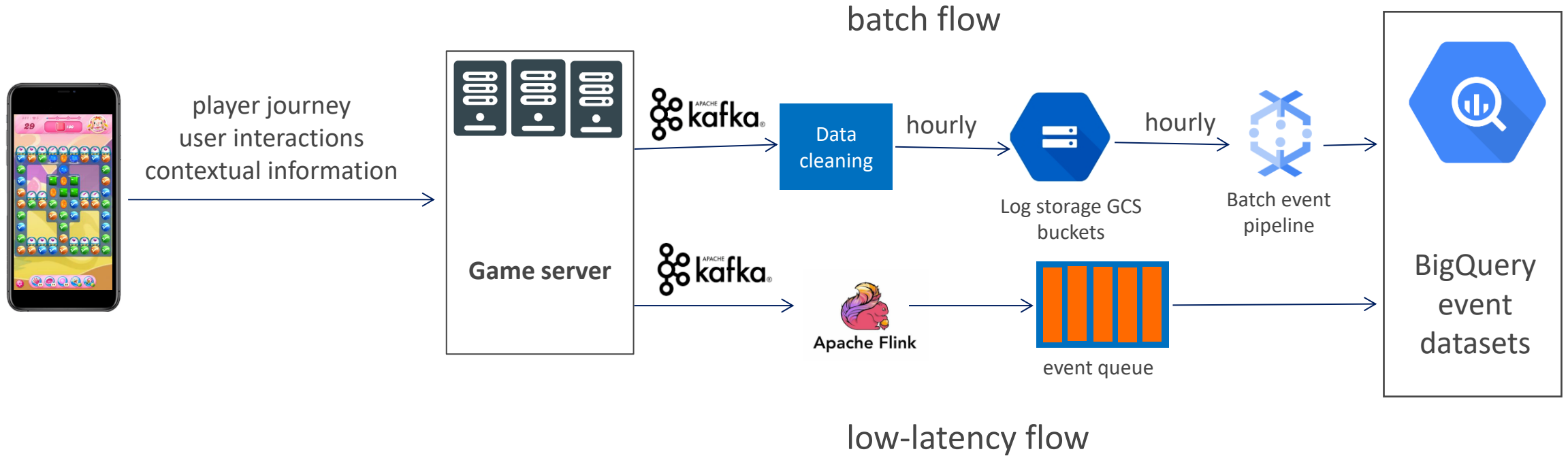
- **Previously:**

- every game feature tracked differently

- **Now:**

- unified template interface and generalizable structures for tracking

Data flow between the client and data warehouse



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Choosing the right way of integration

- **Challenges:**

- Integration between Client <-> Game server <-> Data infra (GCP)
- Predictions freshness (should be always updated, check that they're up to date)
- User experience (not to let the user wait – e.g. when to retrieve? How to cache?)
- Fallback (default) option in case prediction pipeline fails or data cannot be delivered

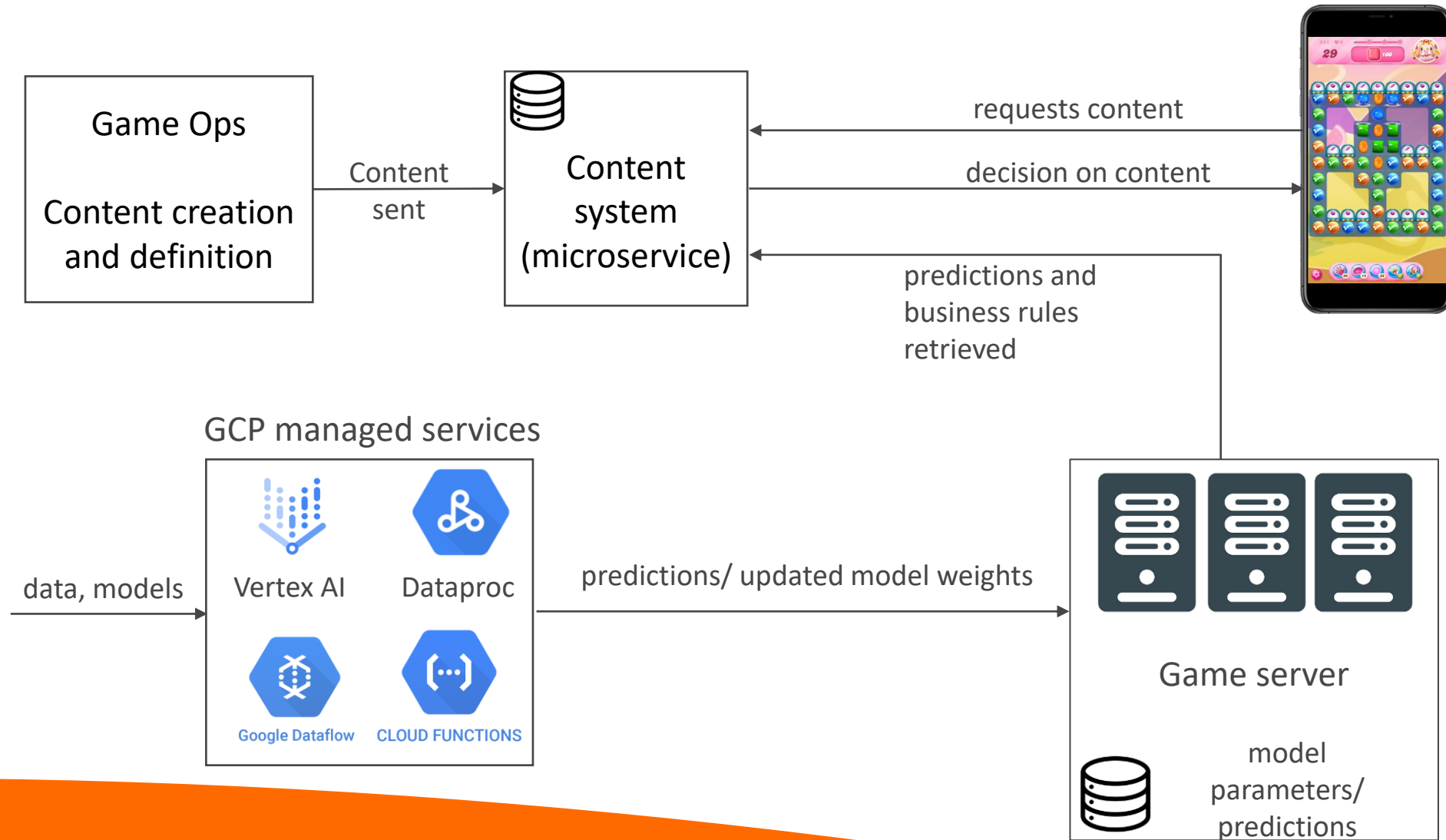
- **Previously:**

- User lists for campaigns (boolean variables of user belonging to campaign, event ...)

- **Now:**

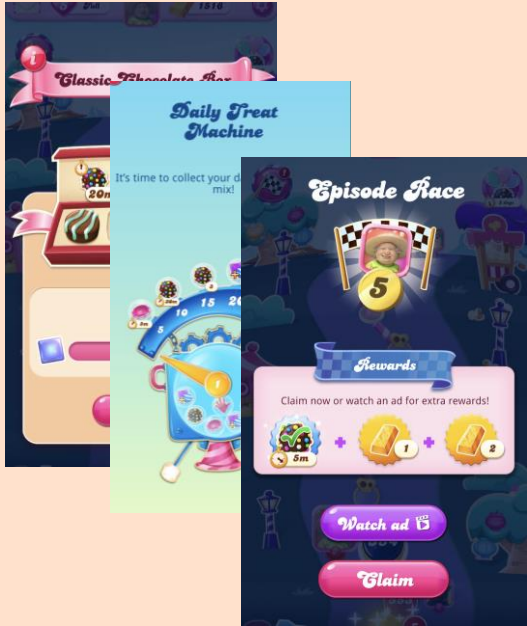
- Delivery of the tuples (user, prediction) to game server that the game client can regularly retrieve

Delivery of predictions from GCP to the game client

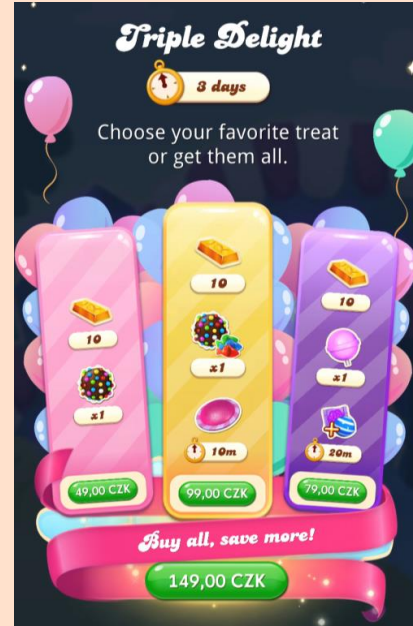


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Use-cases: examples



Optimising which pop-ups to show

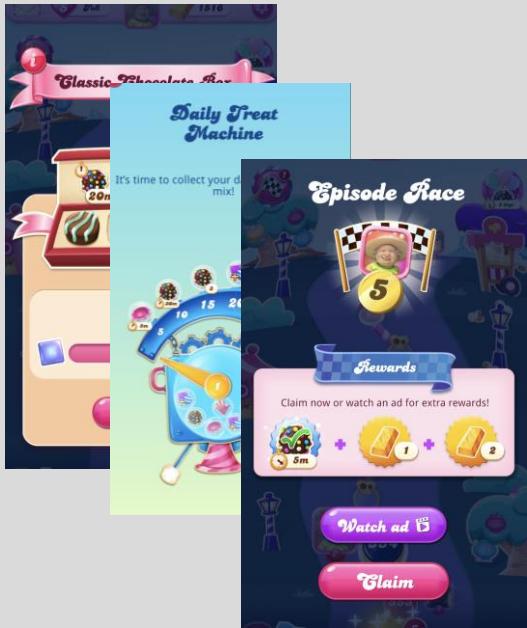


Understanding the user preference for rewards and offers

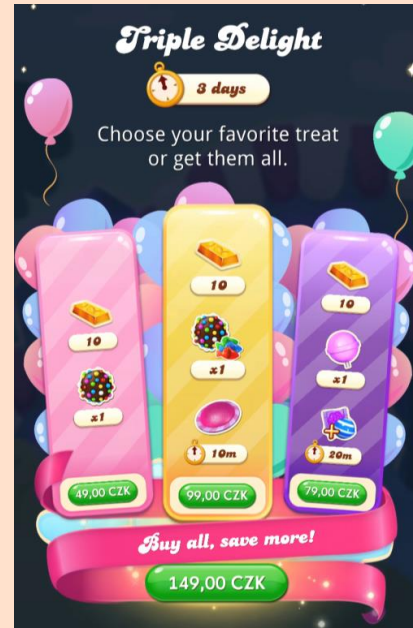


Displaying the right creative assets

Use-cases: examples



Optimising which pop-ups to show



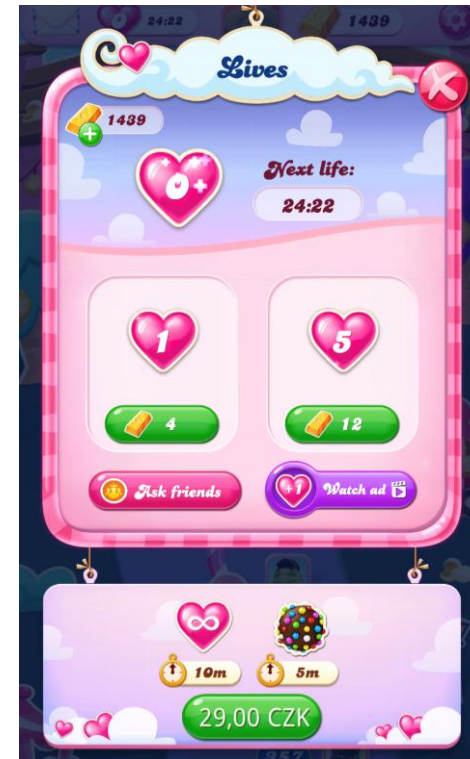
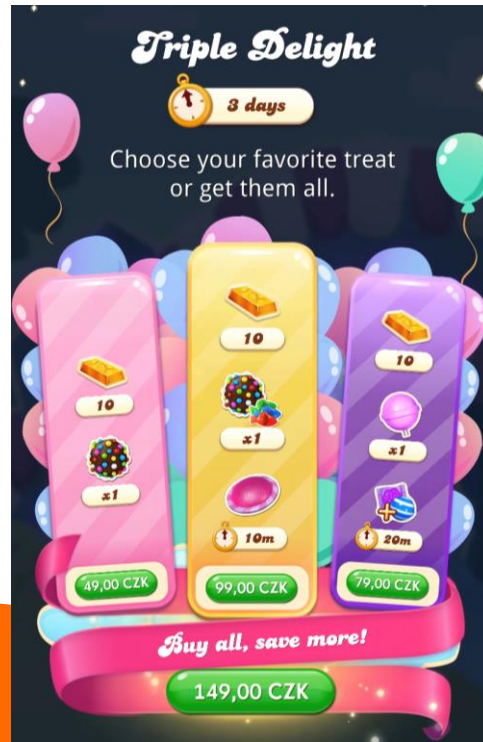
Understanding the user preference for rewards and offers



Displaying the right creative assets

Understanding user preference: Modelling offers and rewards

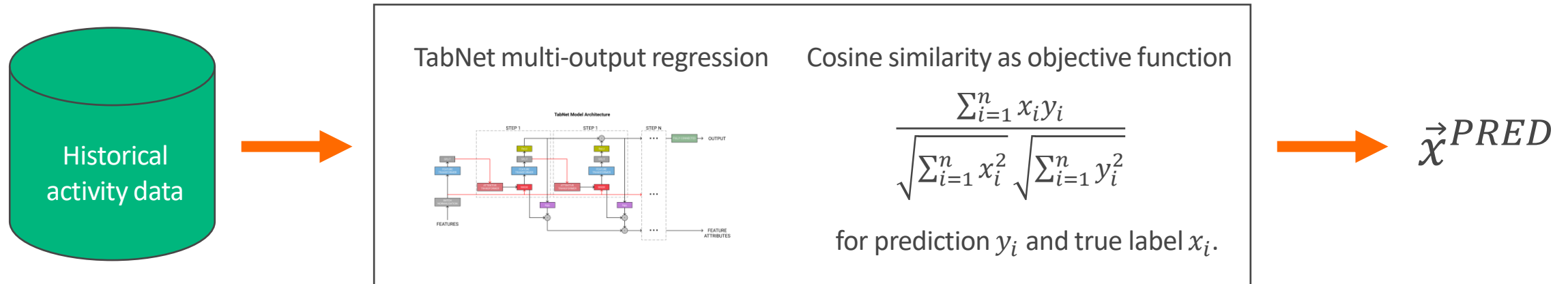
- users are exposed to many popups with generic contents, especially regarding in-app purchases and rewards
- to keep the game more enjoyable and relevant, it is necessary to display relevant content



Understanding user preference: The problem space is dense



Understanding user preference: Modelling via multivariate regression



Arik, S. O., & Pfister, T. (2019). **TabNet: Attentive Interpretable Tabular Learning**. arXiv. <https://doi.org/10.48550/ARXIV.1908.07442>

Katsarou, S., Carminati, F., Dlask, M., et al. (2024). **On a Scale-Invariant Approach to Bundle Recommendations in Candy Crush Saga**. arXiv. <https://doi.org/10.48550/ARXIV.2408.06799>

Tracking and integration implementation

Tracking



Logging events about user behavior, especially interactions in the game (e.g. GUI tracking)



Providing contextual information inside the tracking is essential for modelling



Including client and server timestamps for monitoring any data delays or losses

Integration



Combination of business rules and predictions into a single pipeline



Fallback in case the prediction fails or not delivered



Integrated scalability to be able to consume new predictions (as this is multivariate regression problem)

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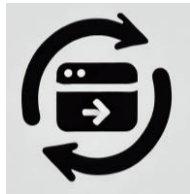
Tracking system design should come before developing AI solutions



Integrating predictions for decision making in existing systems requires robust implementation



Latency as performance metric is essential in systems with many connected components for delivering predictions in time



Caching previous predictions and fallbacks are necessary to prevent missing content

Thank you!



Martin Dlask



Want to discuss tech, explore more ideas or share insights?

Let's continue the conversation!