

# Automatic Generation of Marketing Personas

Extracting insights from social networks

**Supervisor**

Alberto Montresor

**Co-Supervisors**

Carlo Caprini  
Daniele Miorandi

Bachelor Degree in Computer Science

Department of Information Engineering  
and Computer Science

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**Student**

Nicola Farina

# Marketing Personas

*A persona is a fictional character that communicates the primary characteristics of a group of users. [1]*

## pros:

- personalized customer experience
- easier to plan marketing campaigns

## cons:

- long time to create
- high costs

### TRACY CHADWICK



"I'm looking for a forward thinking, forward way of communicating information."

AGE 29  
OCCUPATION Director of Sales  
STATUS Single  
LOCATION Portsmouth, NH  
TIER Multi-use  
ARCHETYPE Creator

Creative

Intelligent

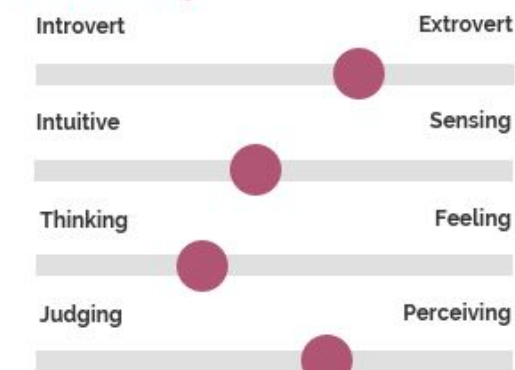
Productive

Hard working

#### Bio

Tracy is a Director of Sales for an ad agency. Her problem is that traditional ads look boring. She is specifically looking for highly customizable designs that can be used to create slides for a presentation. She is motivated to be more creative and have her work stand out.

#### Personality



#### Brands



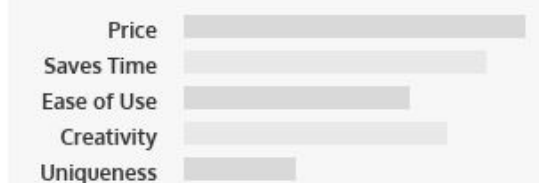
#### Goals

- Sed ut perspiciatis unde omnis iste
- Emo enim ipsam voluptatem quia voluptas sit aspernatur aut odit aut fugit
- Quis autem vel eum iure

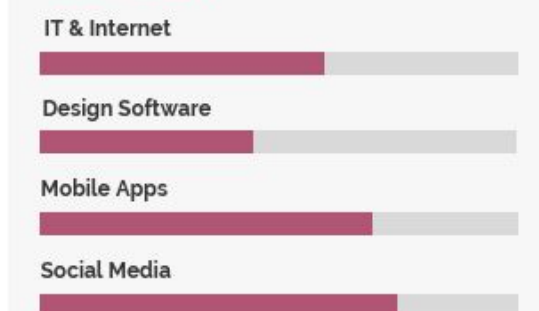
#### Frustrations

- Ut enim ad minima veniam
- Neque porro quisquam est, qui dolorem ipsum
- At vero eos et accusamus et iusto odio

#### Motivations



#### Technology



[1] <https://www.smartinsights.com/persuasion-marketing/marketing-personas/>

# Research Question

Is it possible to **automatically** generate marketing personas through the use of **machine learning**?

## **Automatically:**

- no need for user input

## **Machine learning:**

- clustering
- classification

# State of the Art

Current focus on using **social network data**, from which can be extracted:

## demographics

gender  
age  
location  
job  
income

## behavioral insights

personality  
interests  
attitude



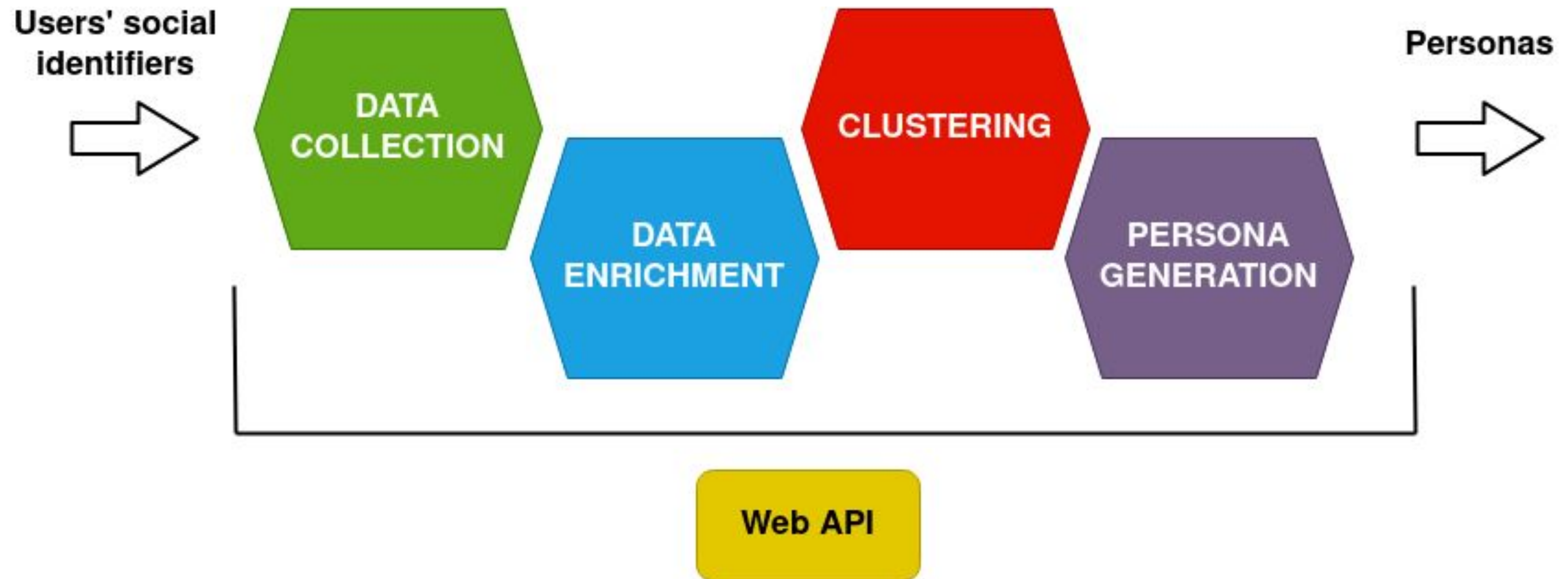
customers **grouped** based  
on such insights

## Legal Basis:

- GDPR compliance

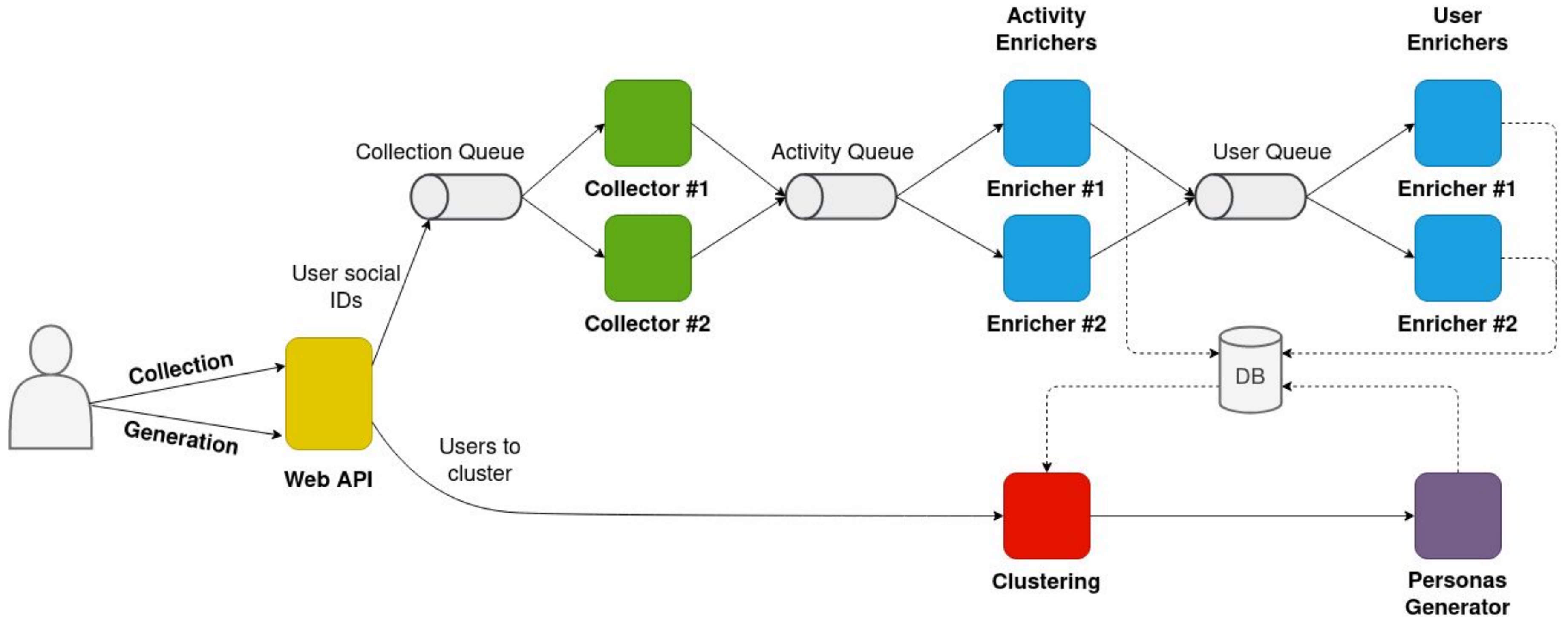


# Solution design

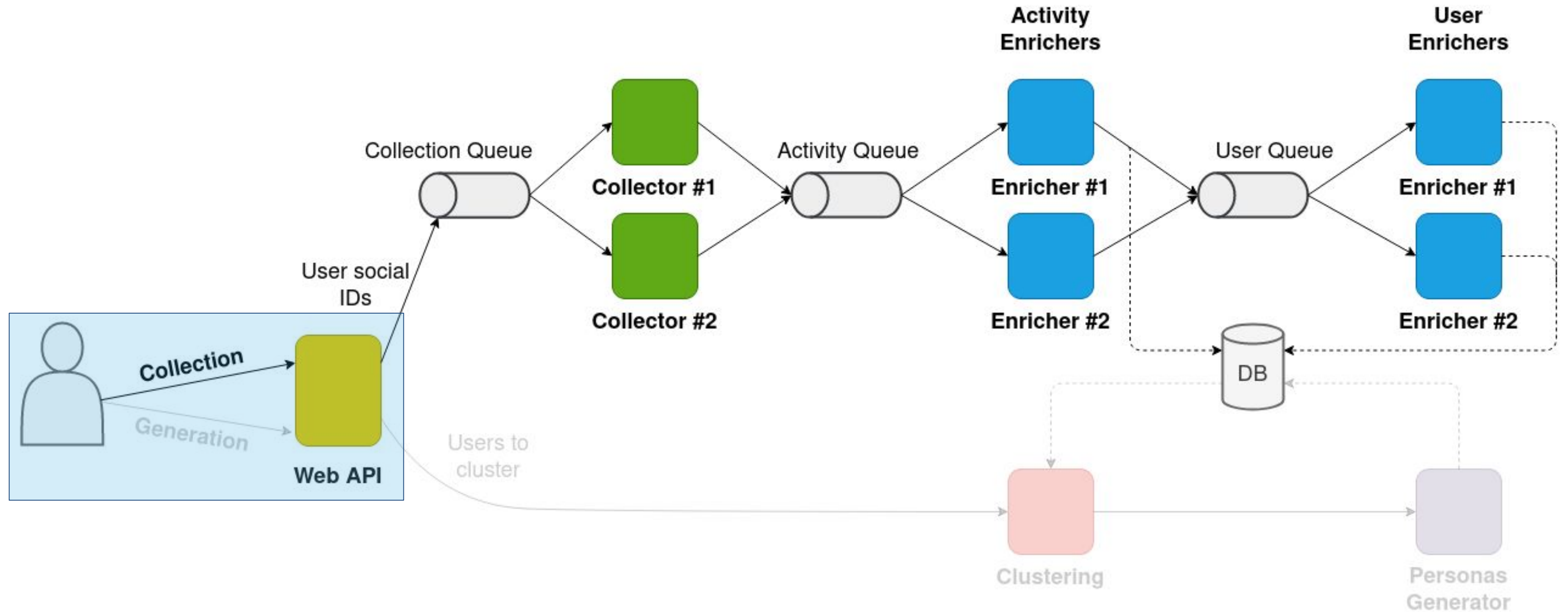




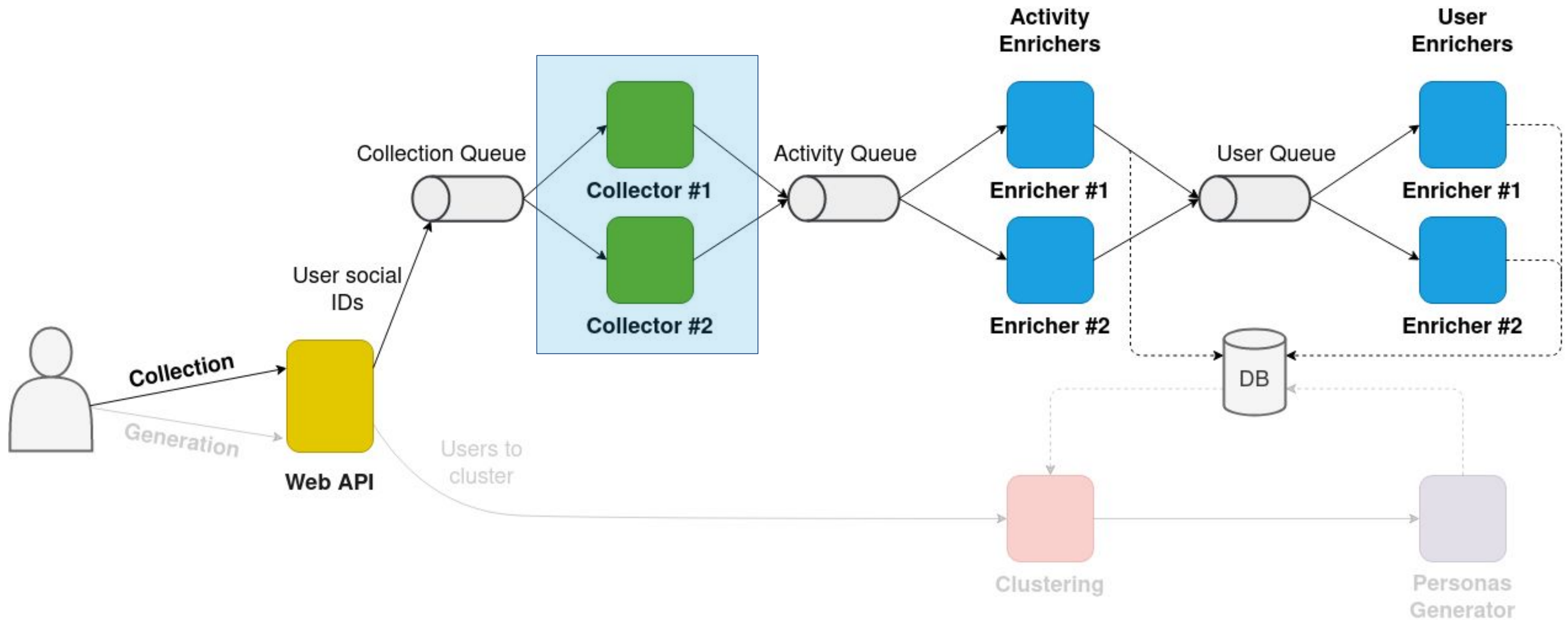
# System Architecture



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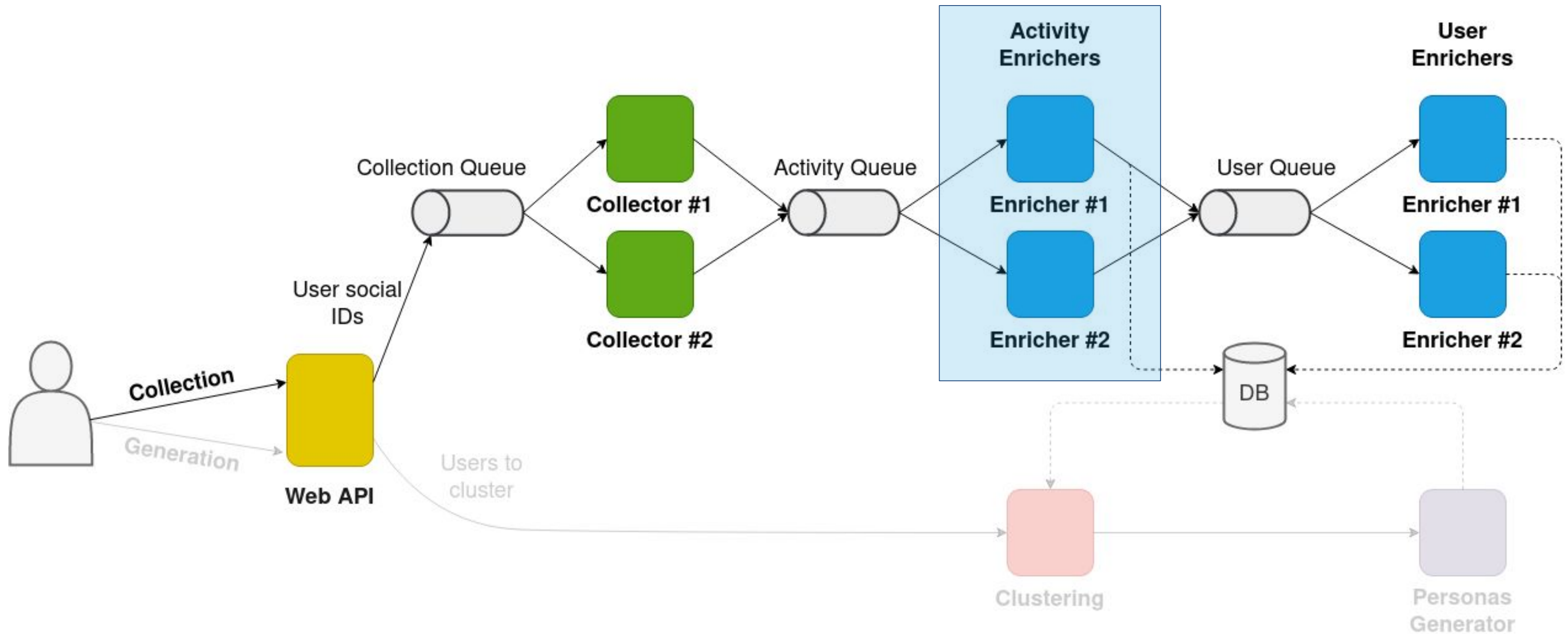


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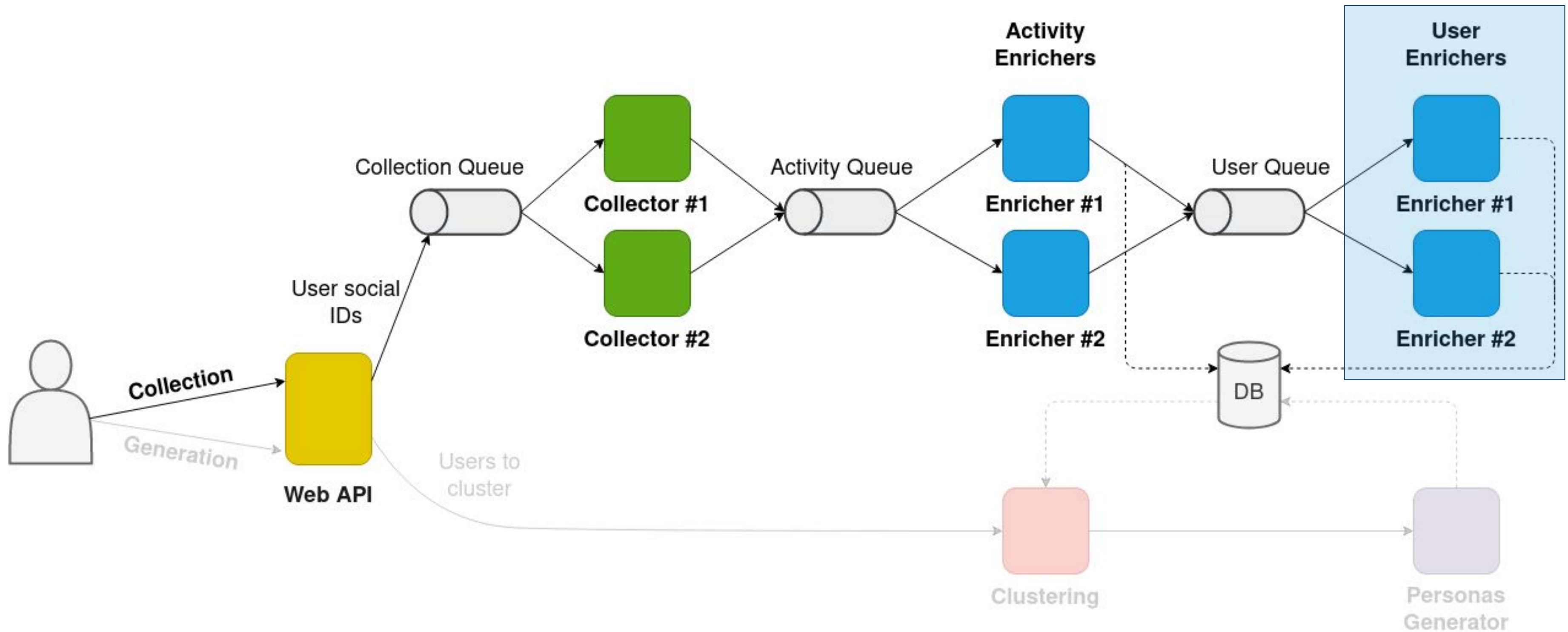




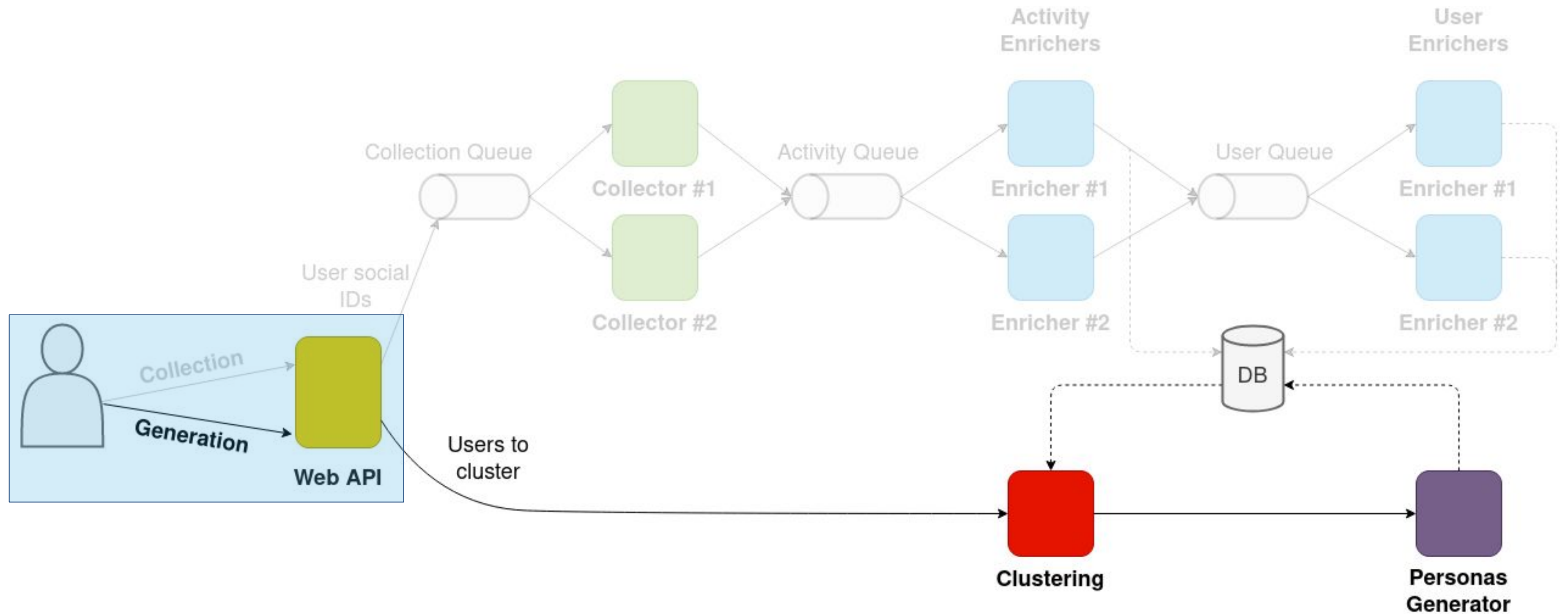
# System Architecture



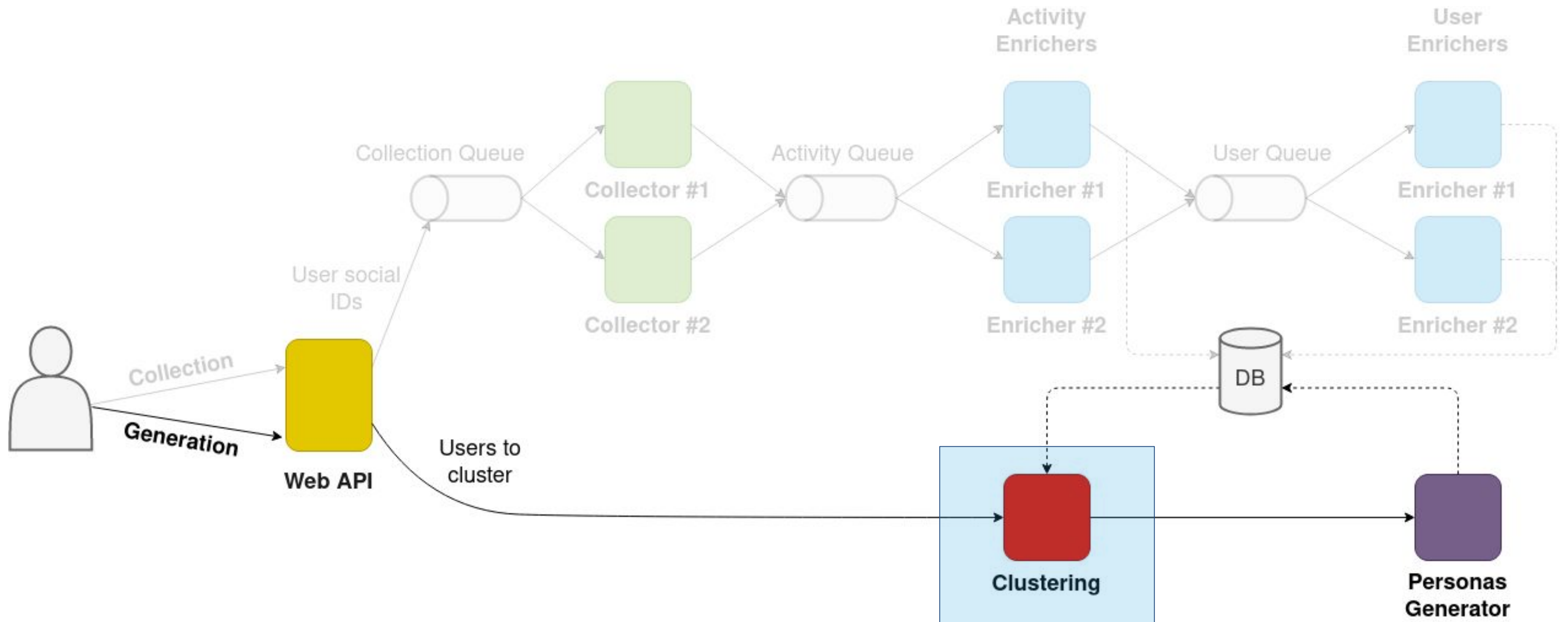
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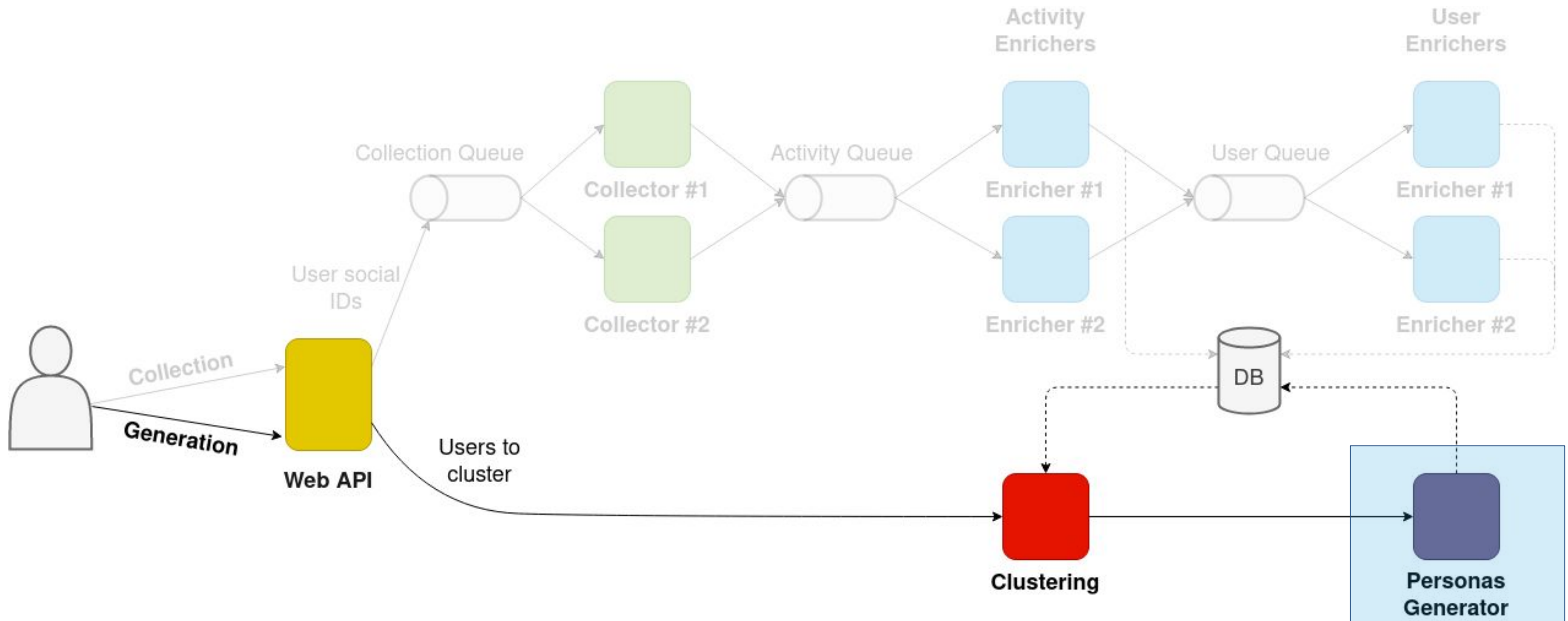


# System Architecture





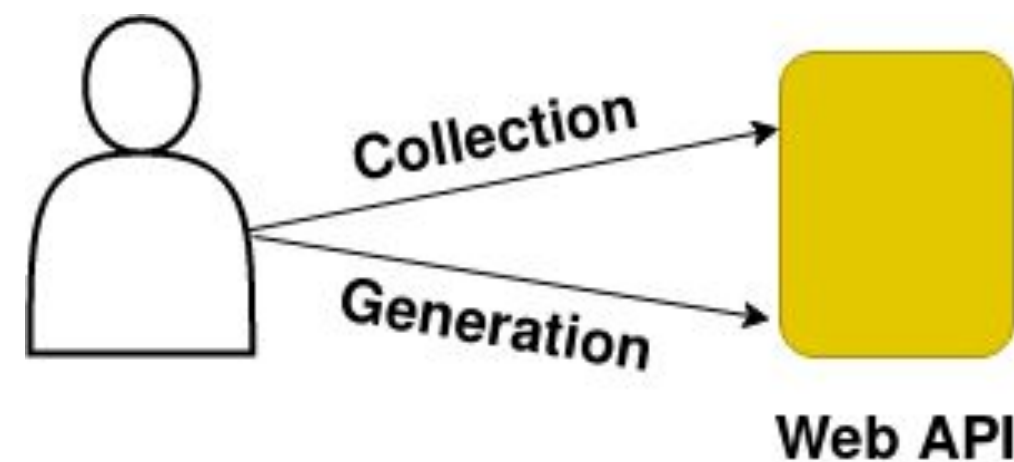
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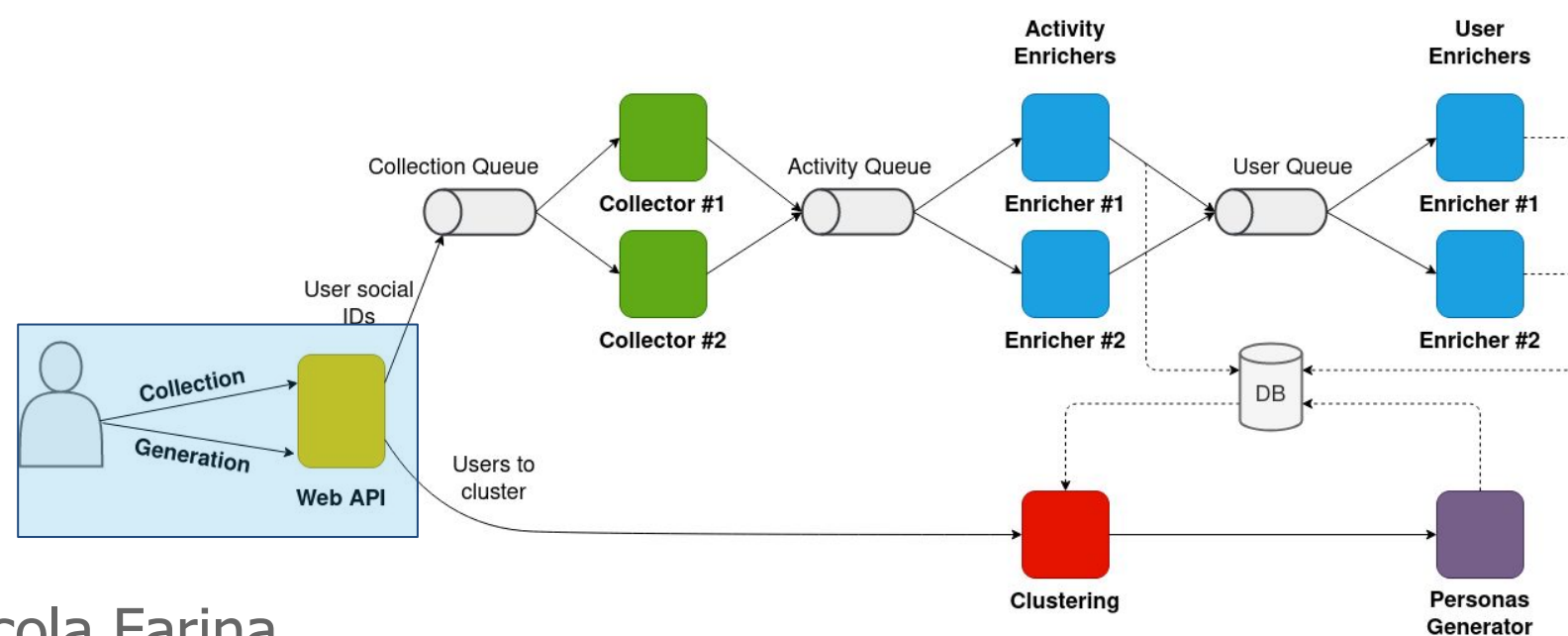


# Web API

- RESTful
- Framework: Flask
- Security: JWT

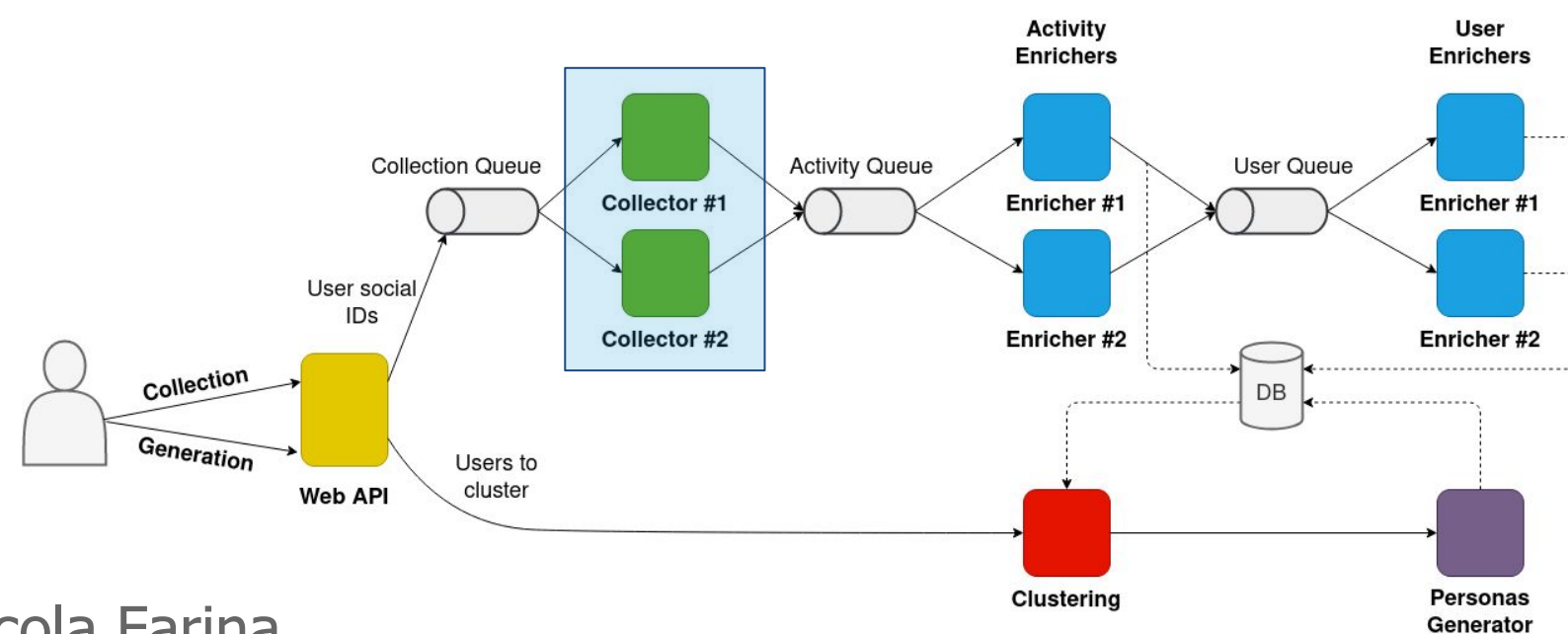
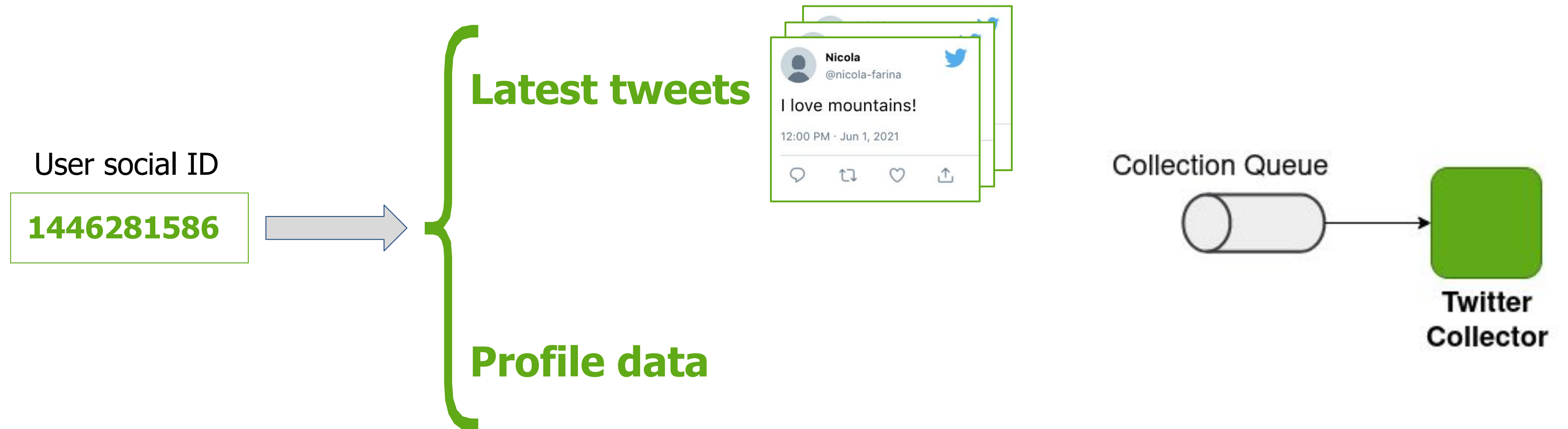


More operations and endpoints are provided (authentication, information retrieval, status checking...)



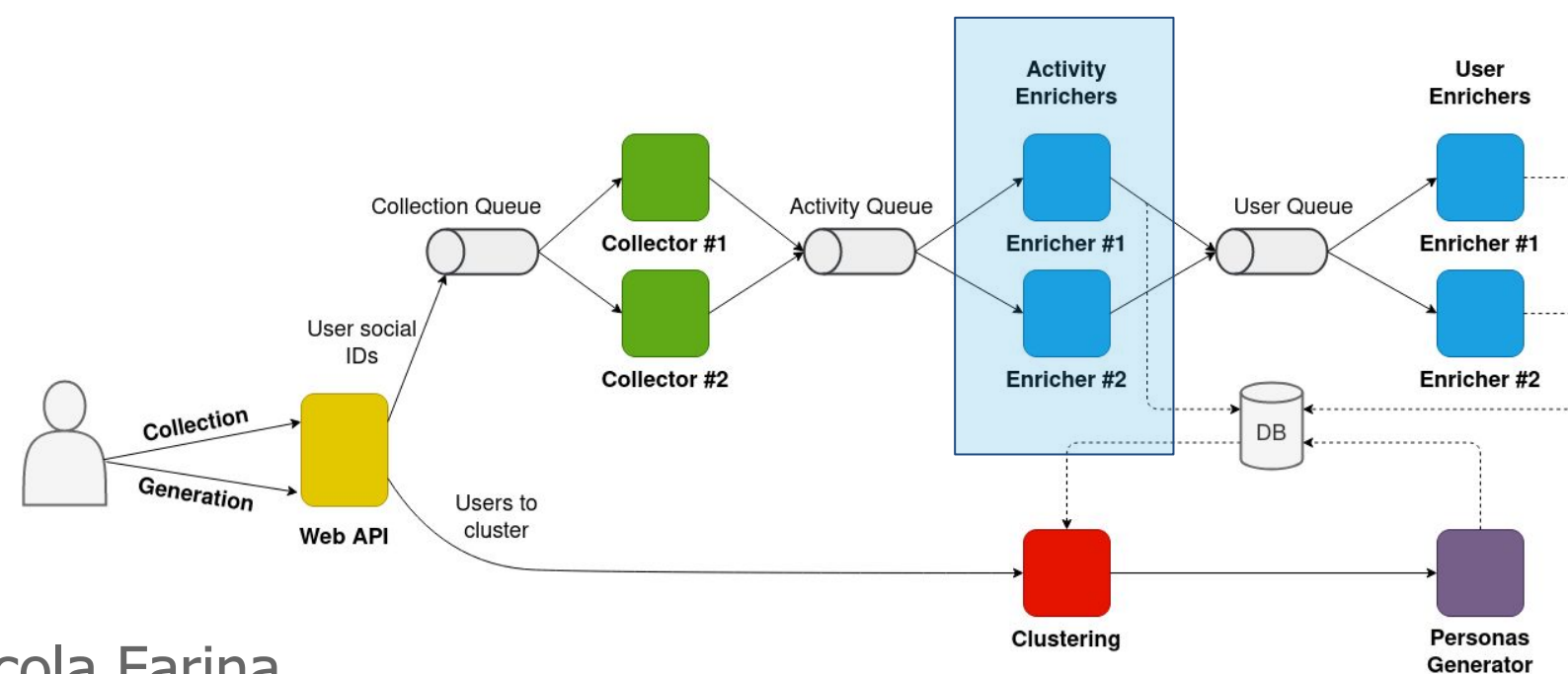
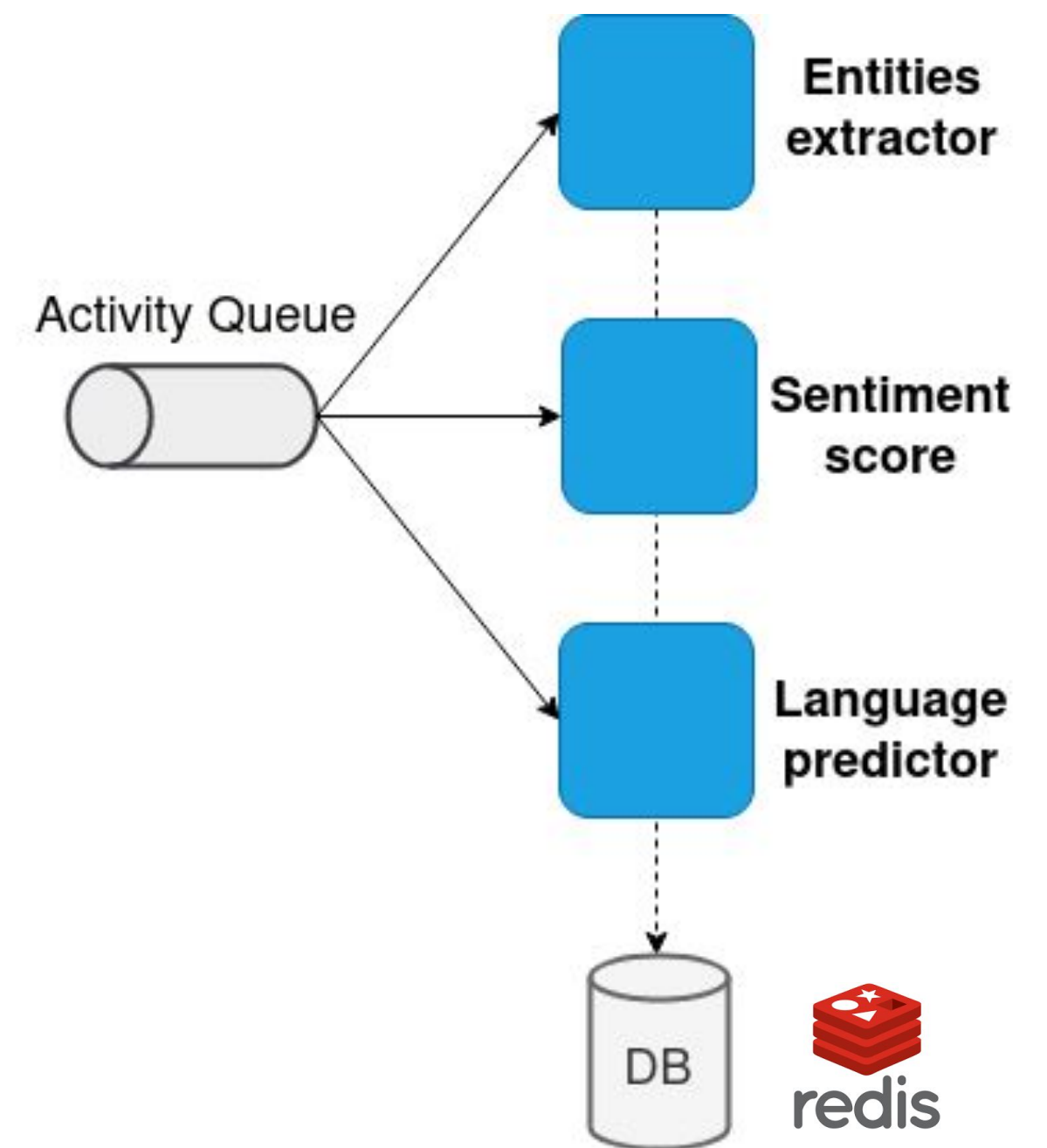
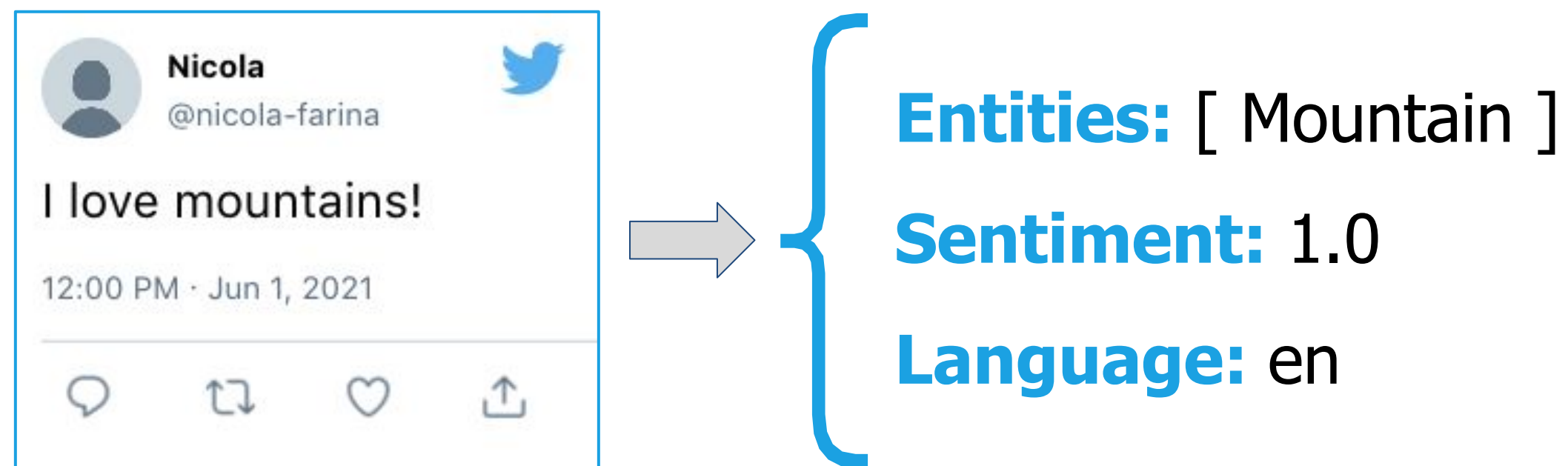
# Collection

- Twitter API

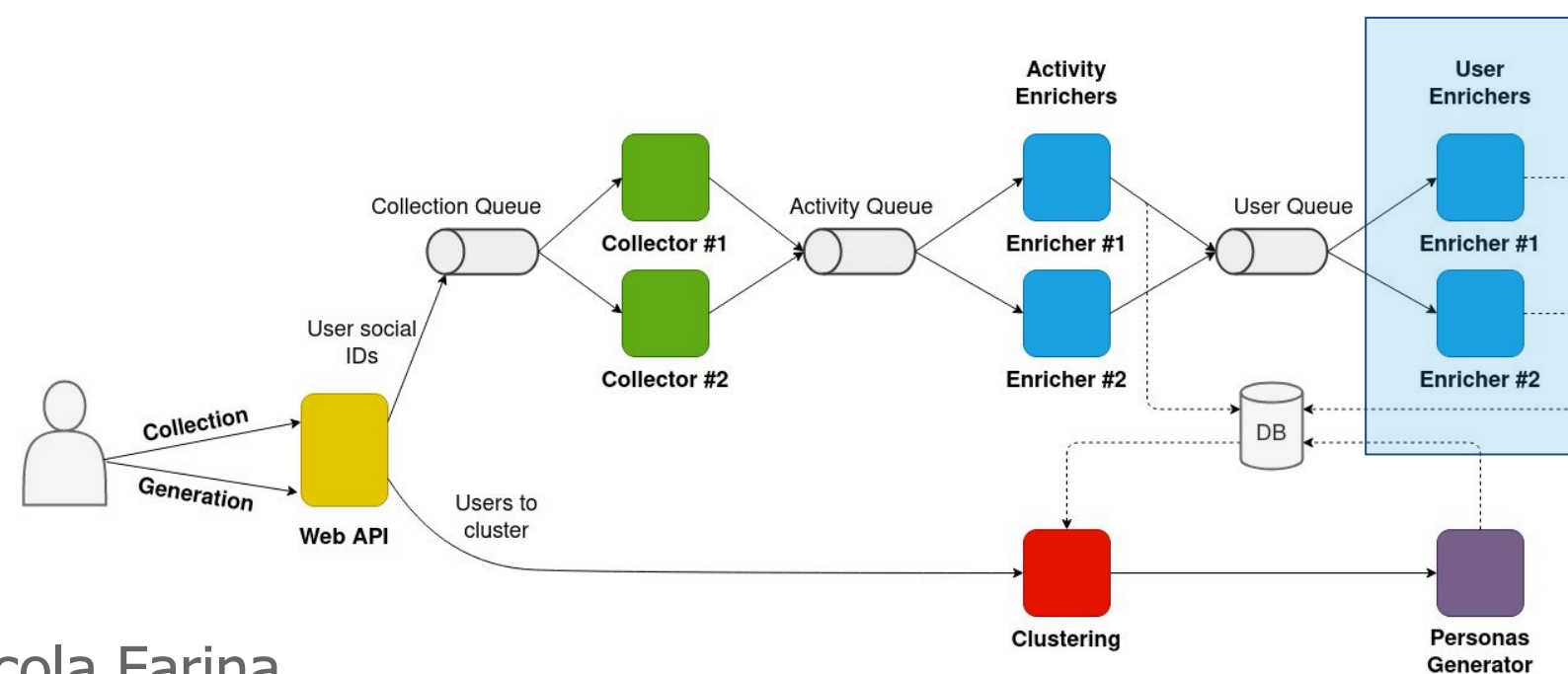
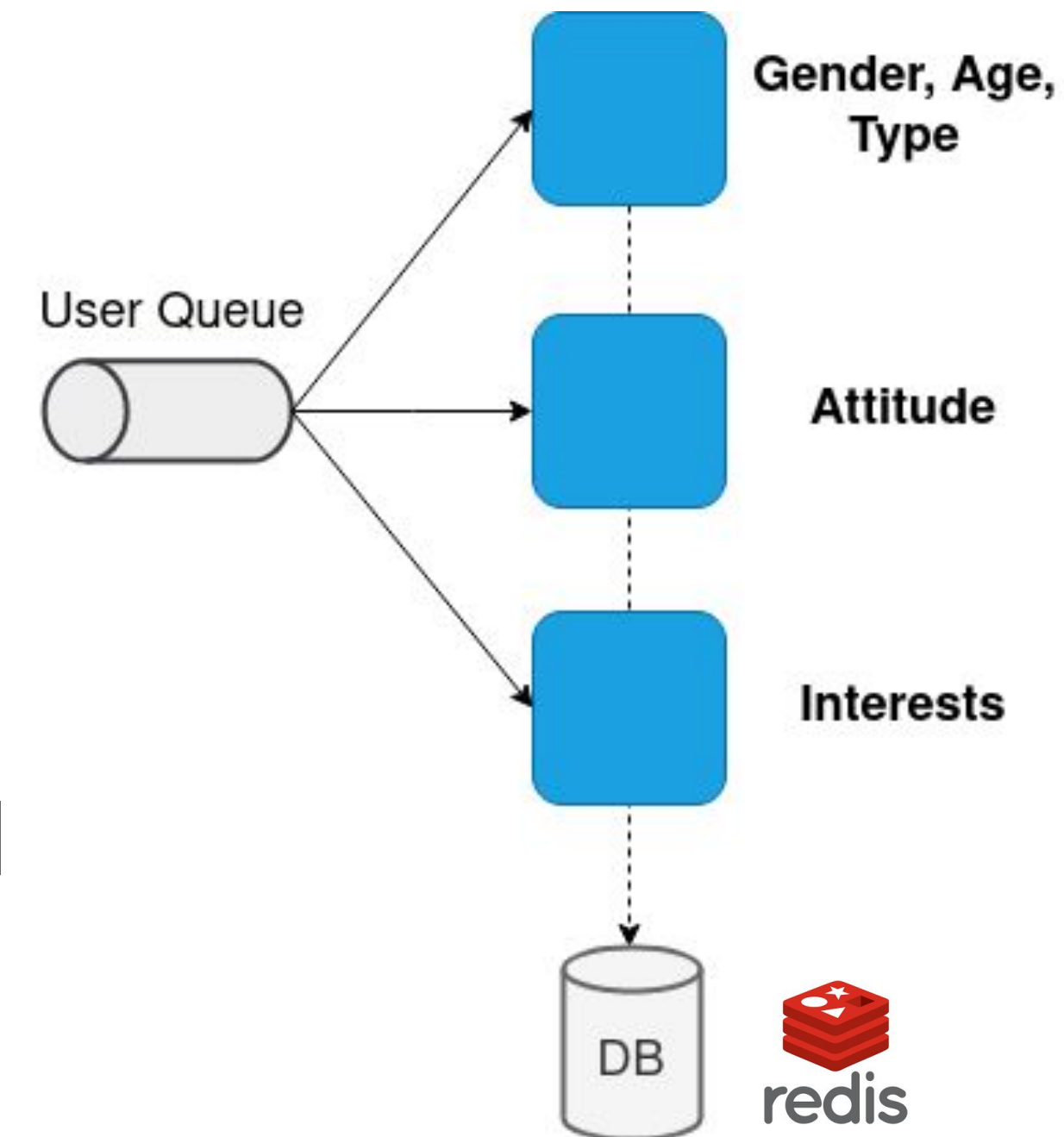
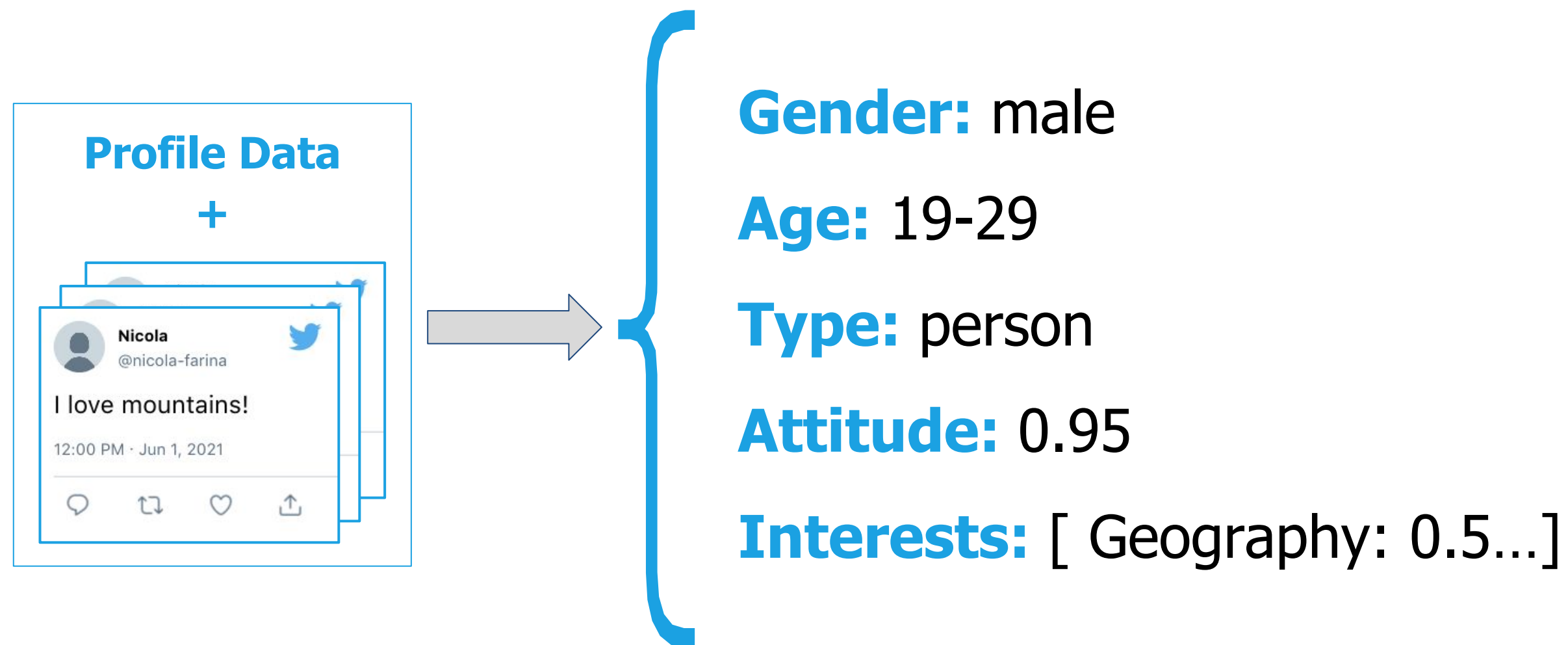


# Activity enrichment

- Dandelion API



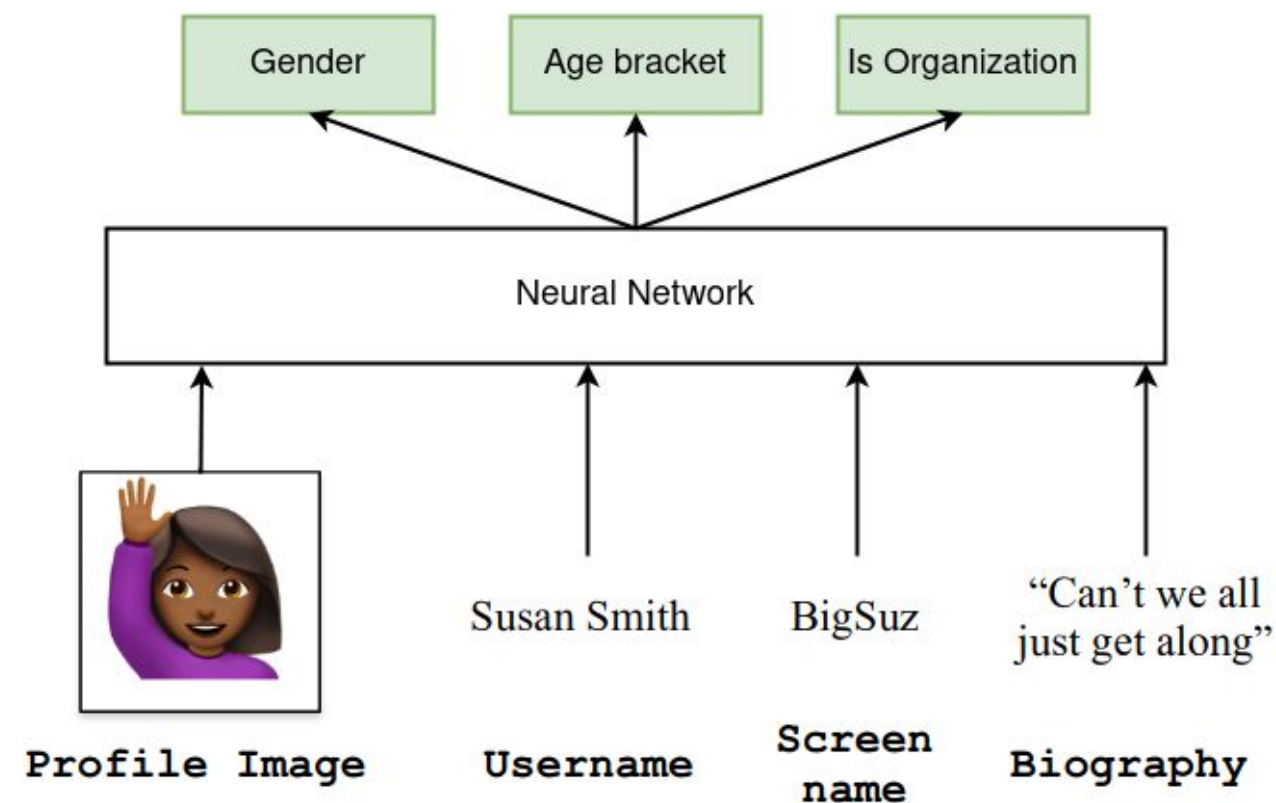
# User enrichment





# Gender, age, type, attitude

## Gender, Age, Type [2]



## Gender (alternative)

Map: First name -> gender

Name	Gender
Marco	M
Stefania	F
Gabriela	F
John	M

## Attitude

Average sentiment score

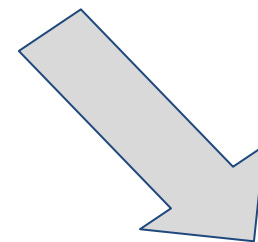
[2] Wang et al., [Demographic Inference and Representative Population Estimates from Multilingual Social Media Data](#)



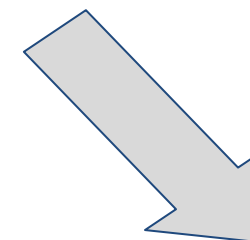
# Interests

**Football: 6**  
**Basketball: 2**  
**Guitar: 2**  
**Mario Draghi: 1**

} **Entity map**



**WIKIPEDIA**  
The Free Encyclopedia

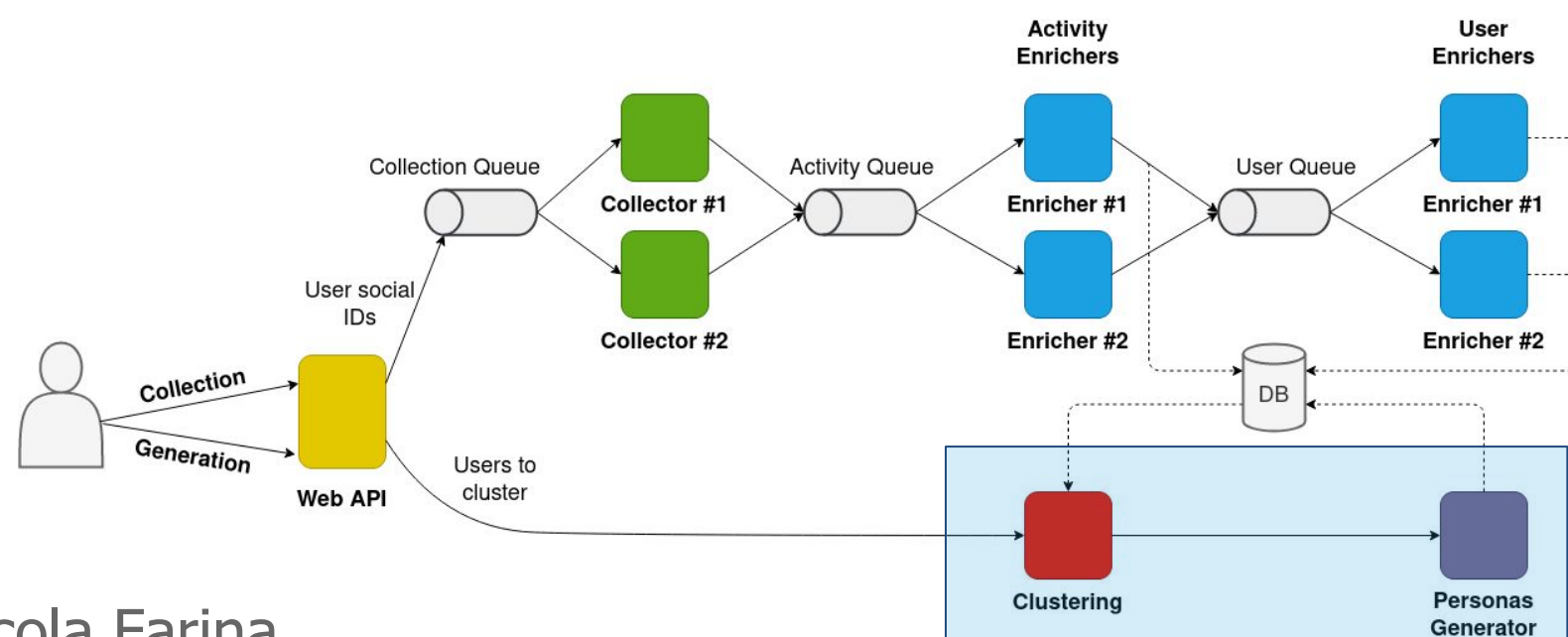
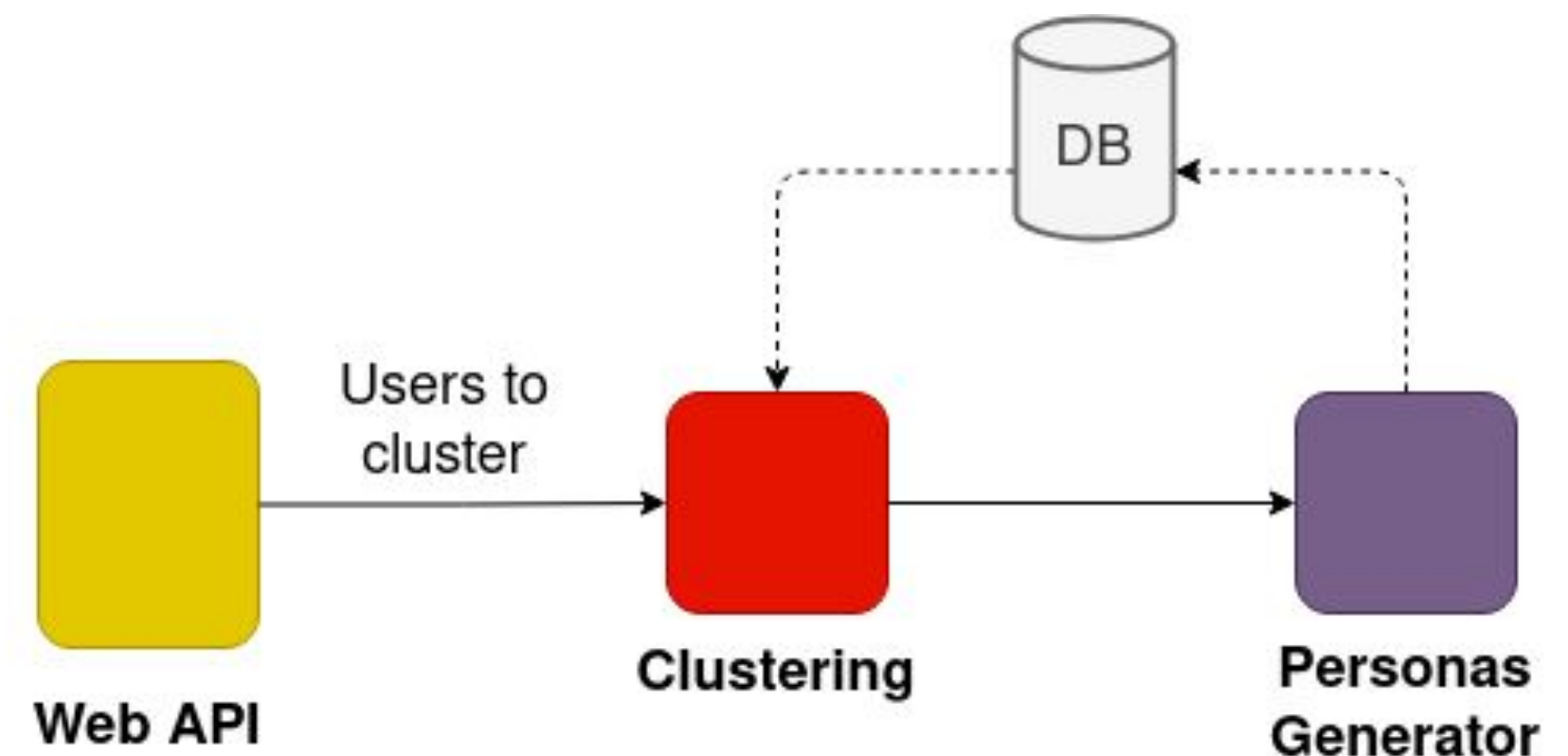


**Interests**

} **Sports: 0.4**  
**Politics: 0.1**  
**Music: 0.2**  
....

# Clustering and Personas Generation modules

- **Clustering:**
  - K-Modes
  - Custom distance metric
  - Centroid: real user
- **Personas generation:**
  - Assign name and photo to each cluster
  - Results via API or web interface

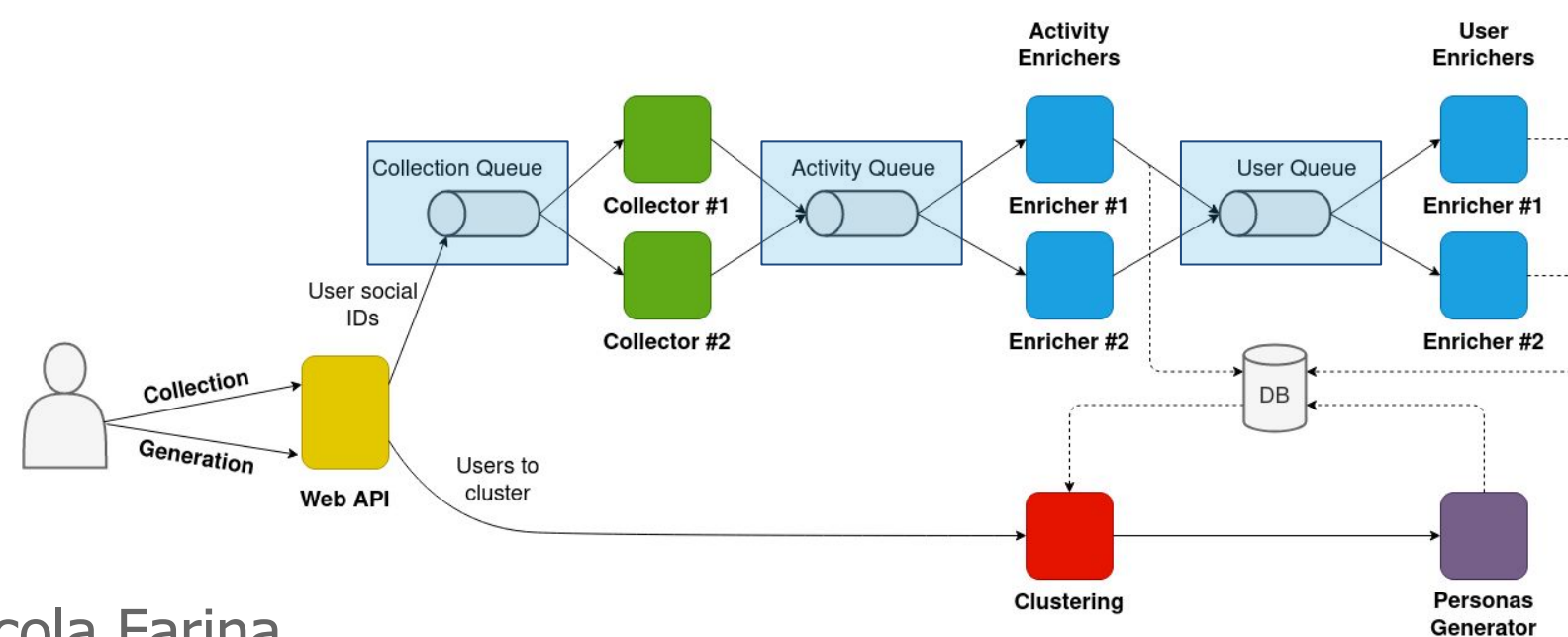
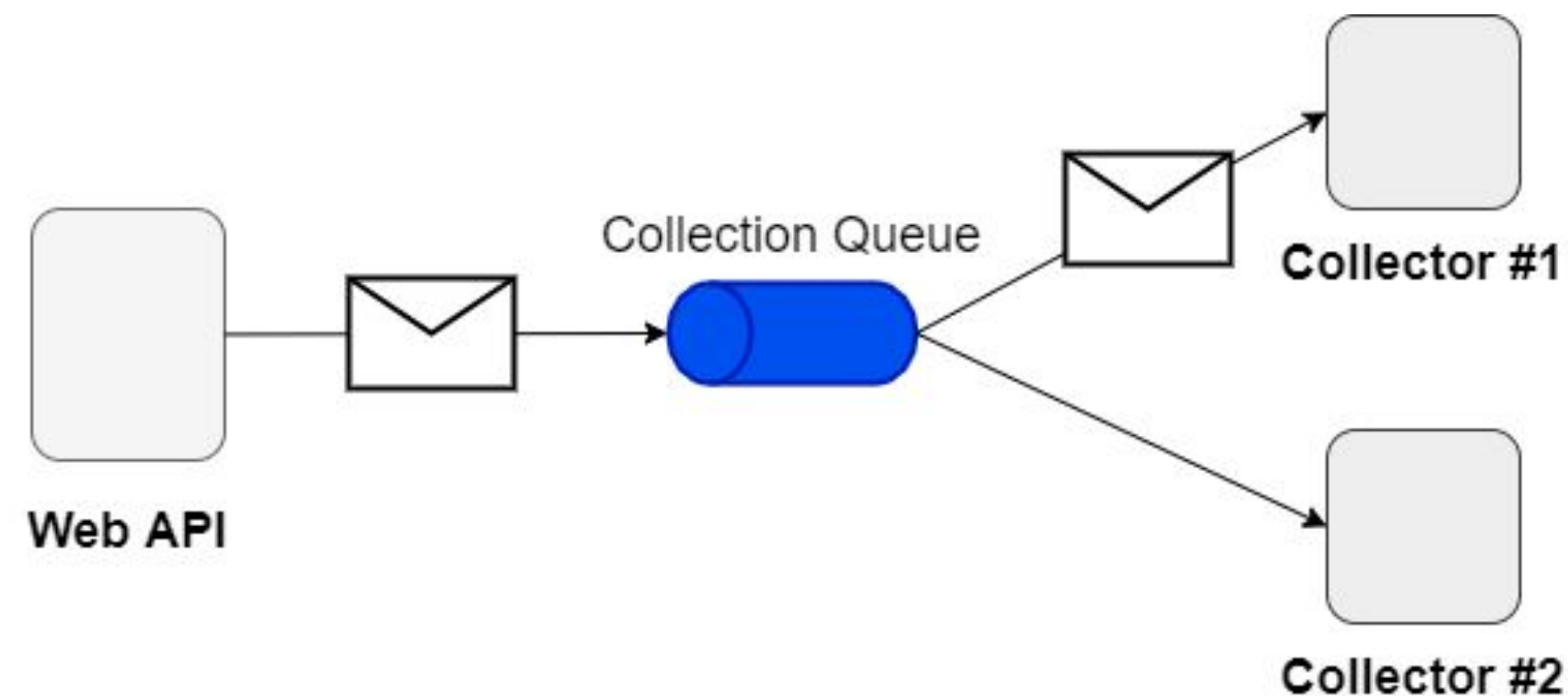


# Persona



# Queue System

- Communication between modules
- Modularity and scalability



# Evaluation: Setup

- **Objectives:**
  - Measure quality of personas
  - Tune parameters:
    - number of activities per user
- **Evaluation dataset:**
  - 90 Twitter profiles of **public celebrities**
    - 30 football players
    - 30 musicians
    - 30 politicians
  - **Ground truth:** gender, age, language, main interest

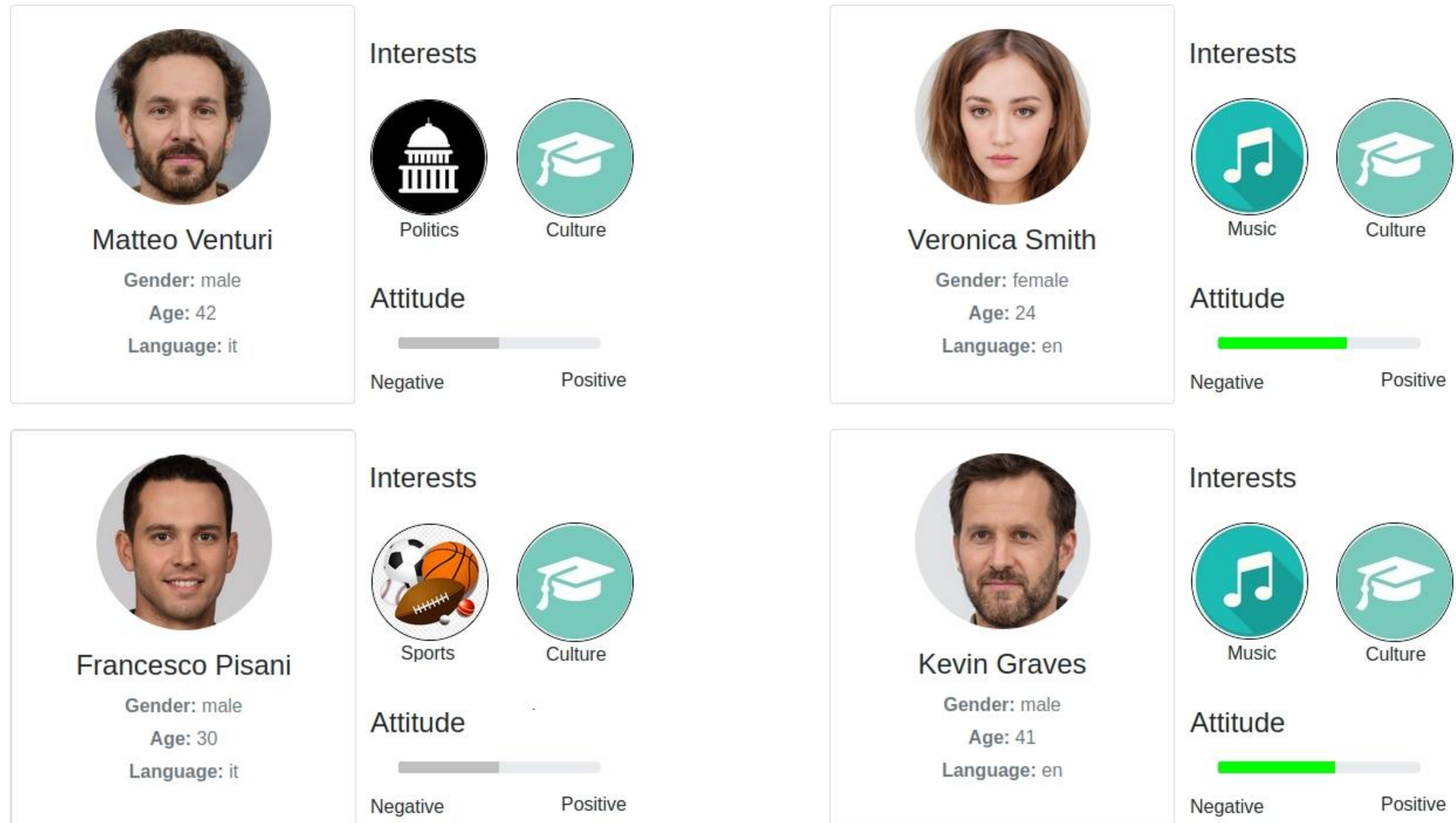


# Evaluation: Optimal number of clusters

- **Trade off:** minimum number of activities (per user) for good clusters
  - Too few: **interests misclassification**
  - Too many: **API rate limitations** (4750 activities per day, Dandelion API)

Activities per user	Optimal number of clusters
20	10
50	4
100	4

# Evaluation: Personas



# Evaluation: Clustering metrics

Cluster	Accuracy	Precision	Recall
Politicians	0.96	0.93	0.96
Musicians (F)	0.97	0.88	1.0
Musicians (M)	0.97	1.0	0.86
Footballers	0.98	1.0	0.96
<b>Global</b>	<b>0.97</b>	<b>0.95</b>	<b>0.94</b>

# Conclusions

- System prototype allows to **automatically** generate **accurate** marketing personas
  - Collect users' data from **Twitter** (e.g. followers of a Twitter page)
  - Enrich users with **gender, age, type, attitude, interests**
  - Cluster users, output **representative users** for each cluster
  - Generate **personas**, one for each representative user
- **Expandable** (add/remove classifiers/data sources) due to queues

## Future work:

- **Provide web service with GUI**
- Add classifiers and data sources





# + : Distance Metric

$$D_{Gower}(x_1, x_2) = \frac{1}{p} \sum_{j=1}^p d_j(x_{1j}, x_{2j})$$

## Ordinal features

$$d_{j,ord}(x_1, x_2) = \frac{|rank(x_{1j}) - rank(x_{2j})|}{range_j}$$

## Numerical features

$$d_{j,num}(x_1, x_2) = \frac{|x_{1j} - x_{2j}|}{range_j}$$

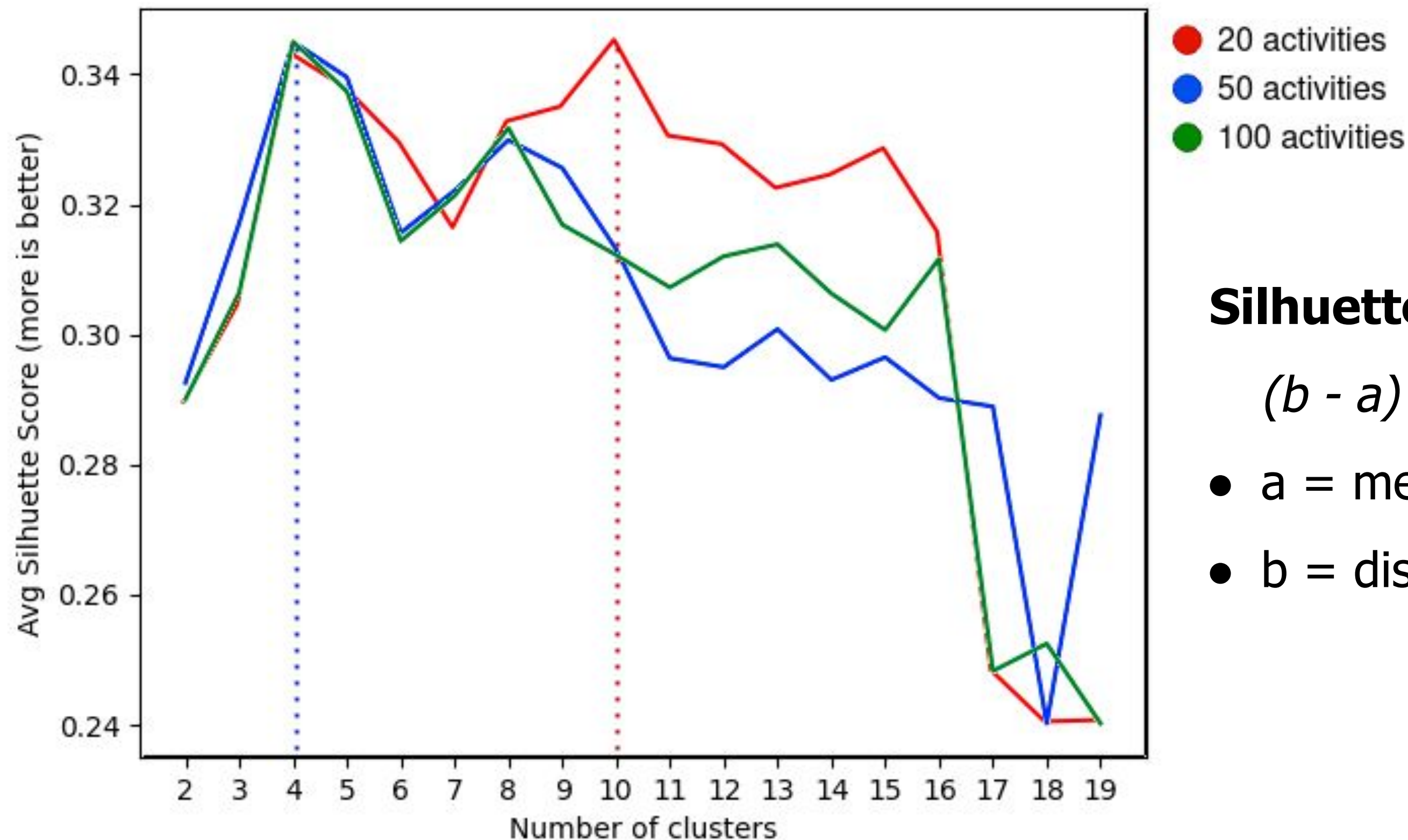
$$d_{j,nom}(x_1, x_2) = \begin{cases} 1 & \text{if } x_{1j} \neq x_{2j} \\ 0 & \text{otherwise} \end{cases}$$

## Nominal features

## Weights

*Gender* = 0.5   *Age* = 0.5   *Language* = 0.3   *Interests* = 13   *Attitude* = 0.3

# + : Optimal number of clusters



**Silhouette score** for a sample:

$$(b - a) / \max(a, b)$$

- $a$  = mean intra-cluster distance
- $b$  = distance to nearest cluster

## + : Evaluation metrics

$$\textit{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (\textit{Fraction of correct predictions})$$

$$\textit{Precision} = \frac{TP}{TP + FP} \quad (\textit{What portion of positive predictions was actually correct})$$

$$\textit{Recall} = \frac{TP}{TP + FN} \quad (\textit{What portion of actual positives was correctly predicted})$$

# + : Gender, age, type classifier

