PlateClick

Bootstrapping Food Preferences Through an Adaptive Visual Interface

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the small data lab

MOTIVATION

Food preferences learning is important!

Health and Life

Obesity 113M

HBP 50M

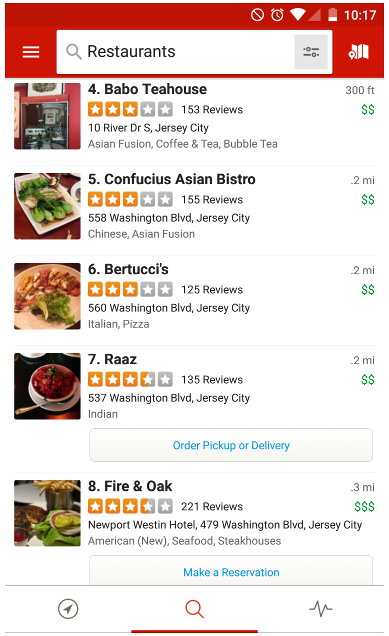
Diabetes 15M

*Number of Americans Living with Diet-and Inactivity-Related Diseases

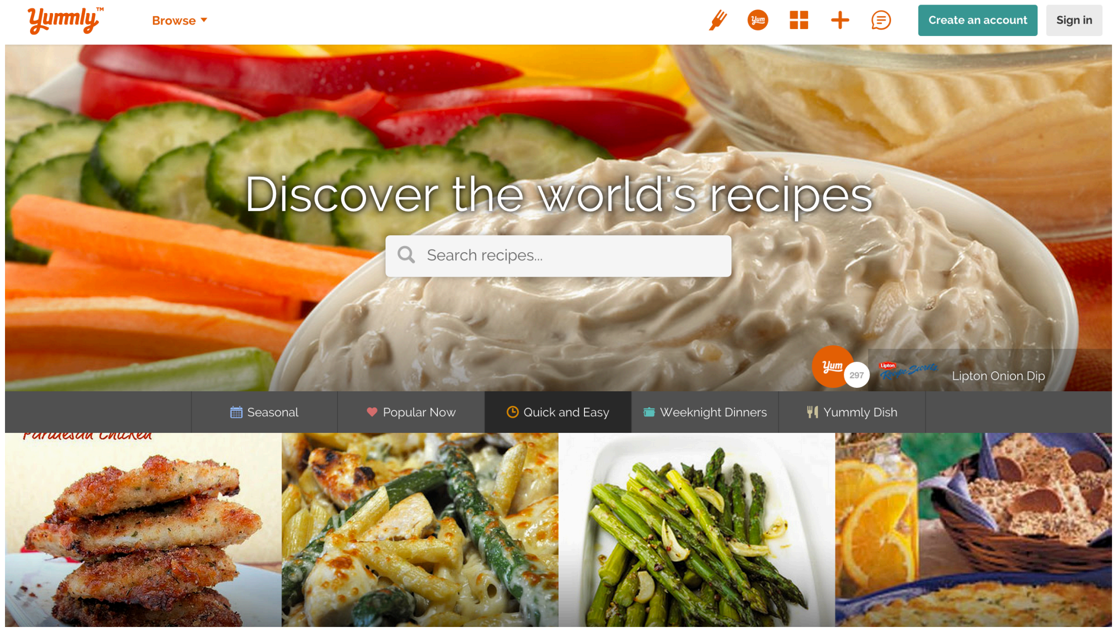
Unflavored Healthy diet recommendations are of NO Benefit!

Social Media and Commerce

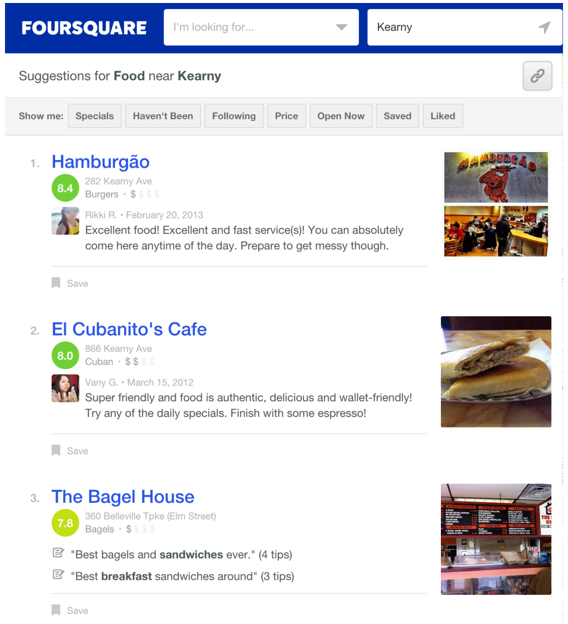
yelp



Yummly

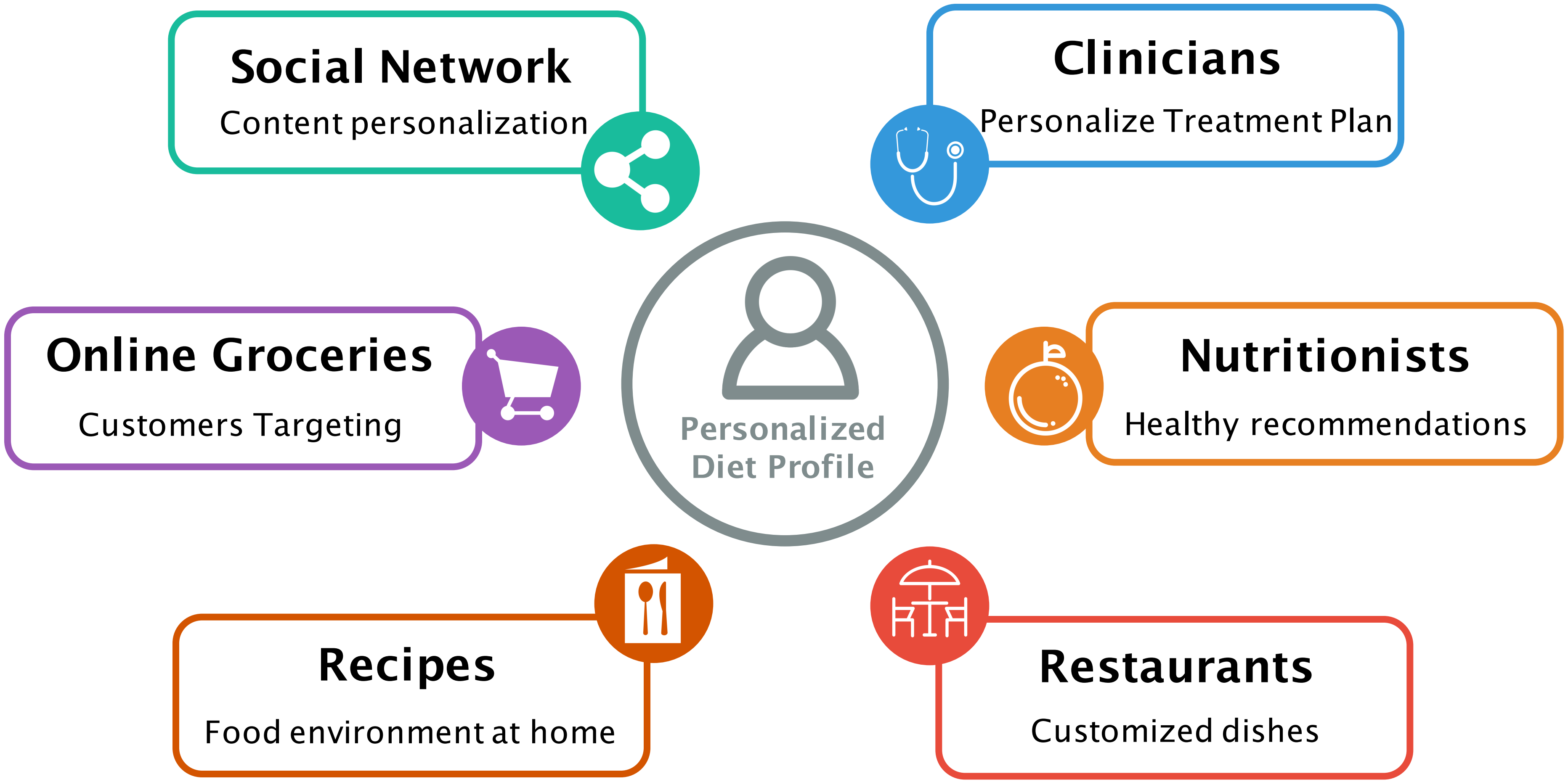


FOURSQUARE



Personalized diet profile is the Key to user experience!

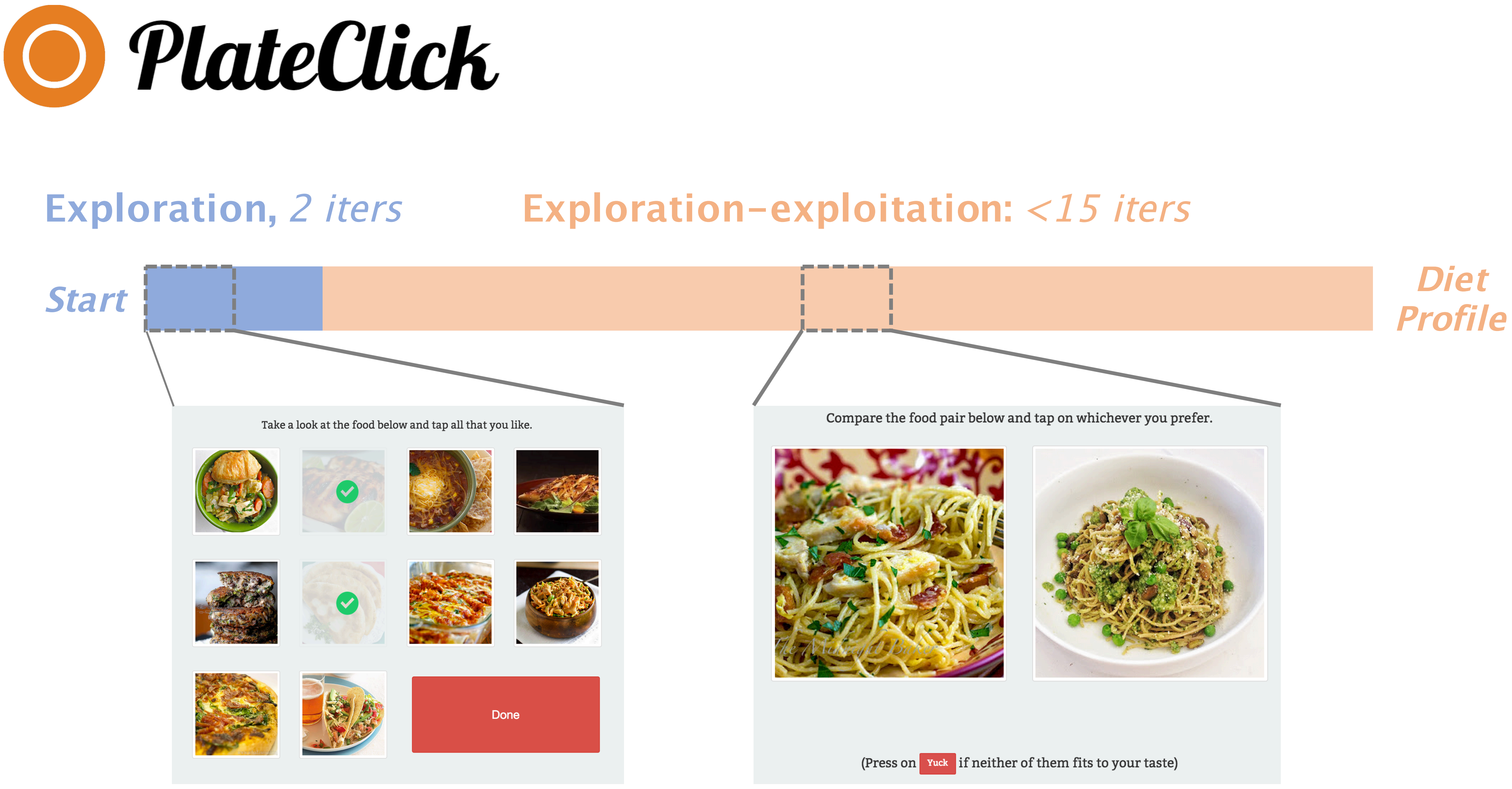
Our Vision



Social Network
Content personalization
Clinicians
Personalize Treatment Plan
Online Groceries
Customers Targeting
Personalized Diet Profile
Nutritionists
Healthy recommendations
Recipes
Food environment at home
Restaurants
Customized dishes

OUR SOLUTION

An adaptive visual interface



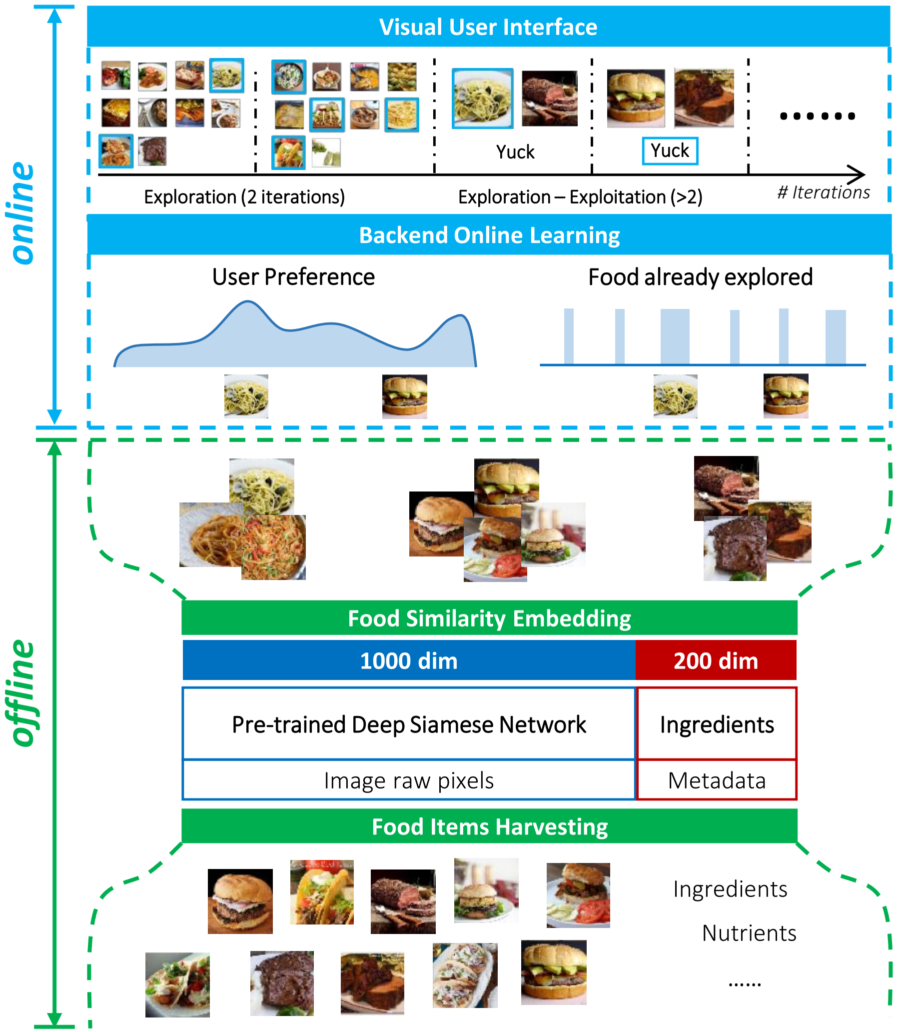
10 food items

Pairwise Comparison

PlateClick

- ✓ **Efficient:** *completed within a minute.*
- ✓ **Visual interface:** *low cognitive load, personalized and legible.*
- ✓ **Preference Elicitation:** *NO history required, NO ratings.*
- ✓ **Deep understanding of food images.**
- ✓ **Novel Online Learning Framework.**

System Design



Online Learning

Online Learning framework (LE + EE)

- ➢ What images to present to the user?
- ➢ How to update users' preferences?

Food Similarity Embedding

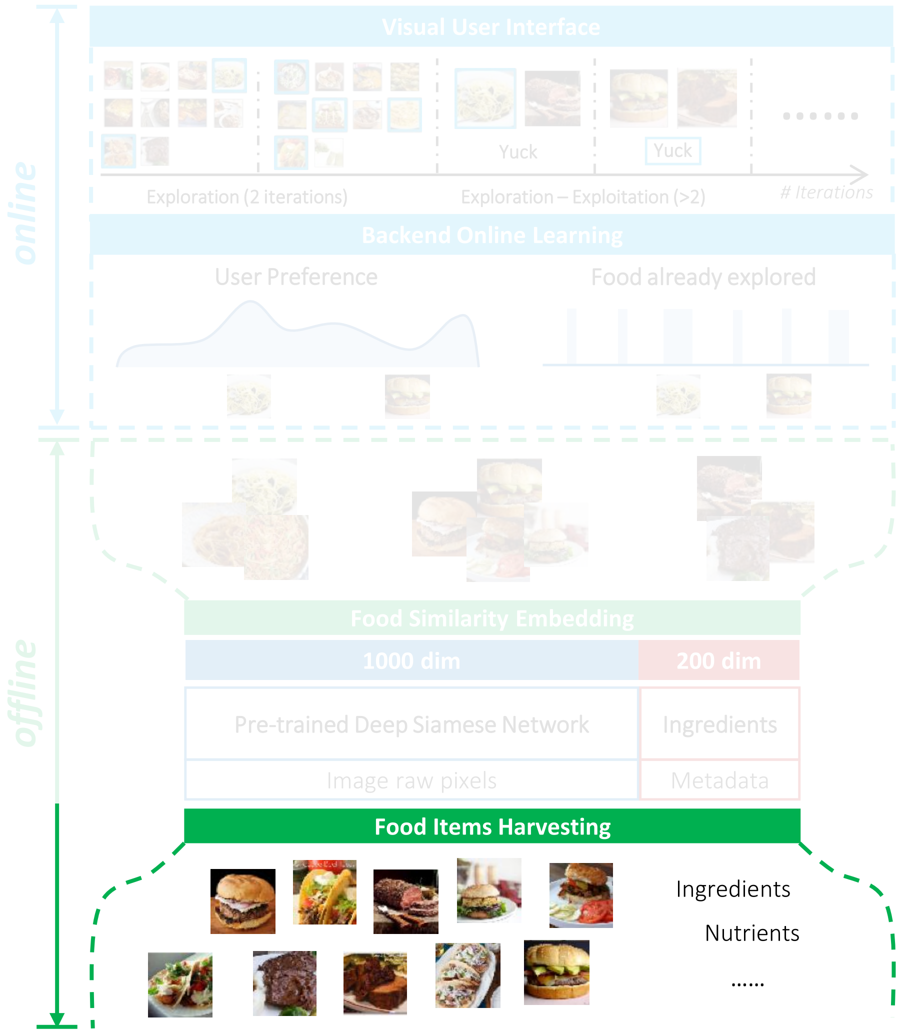
Users have **close** preferences for **similar** items

- ➢ Feature representation that can reflect similarities

Food Items Harvesting

- ➢ Food images and metadata.

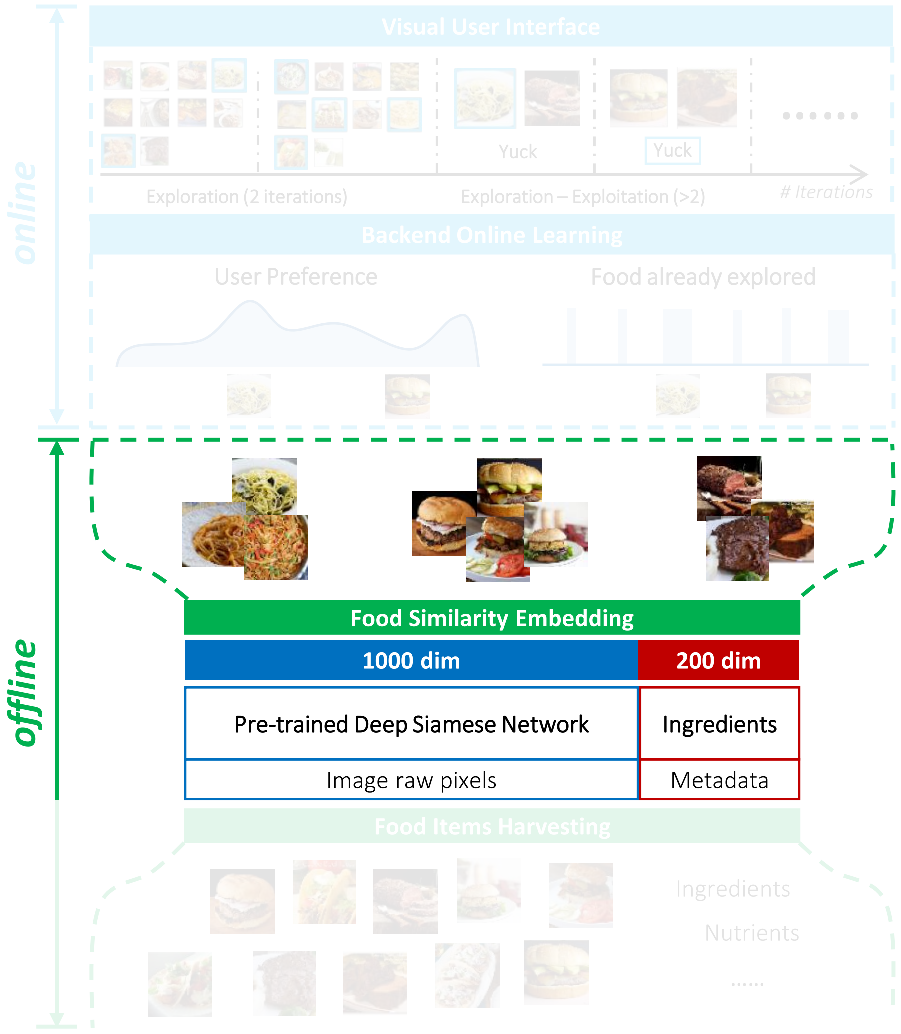
System Design: *offline*

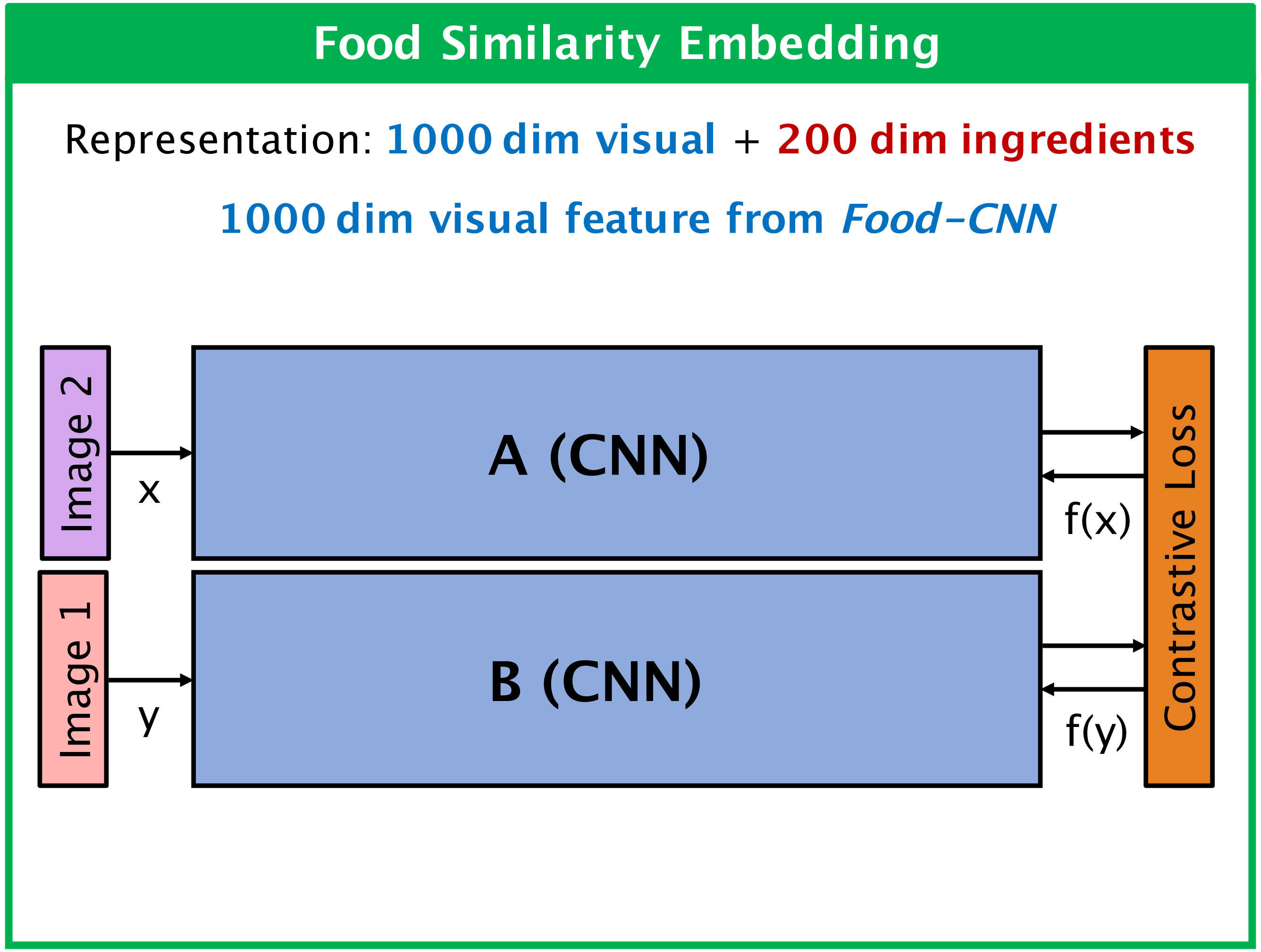


Food Items Harvesting

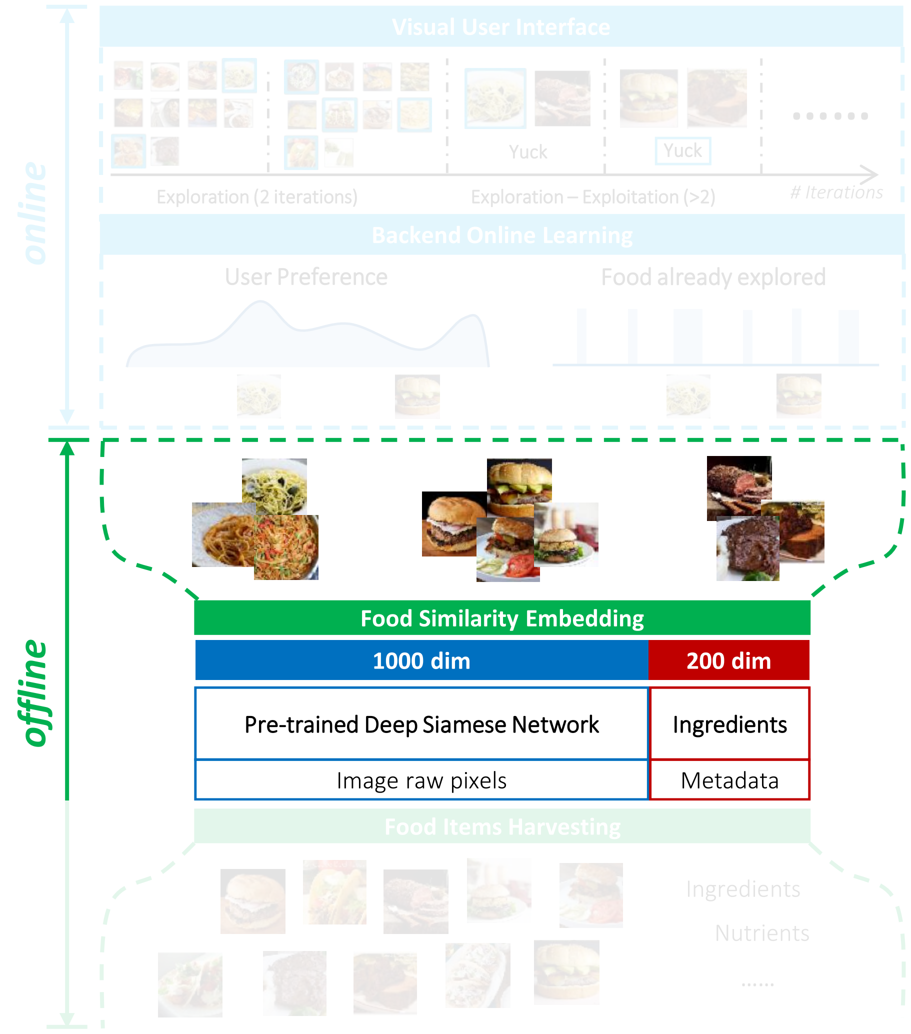
- **12,000** food items from Yummly API.
- Images + Metadata (ingredients, nutrients etc.)
- Outliers filtering, **10,028** items were used.

System Design: *offline*





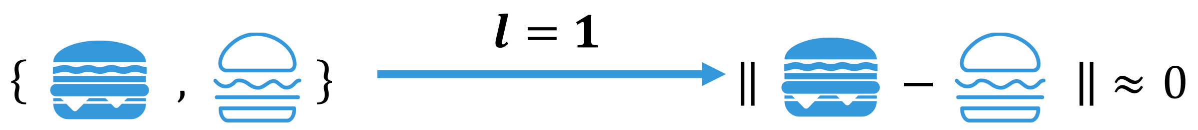
System Design: *offline*



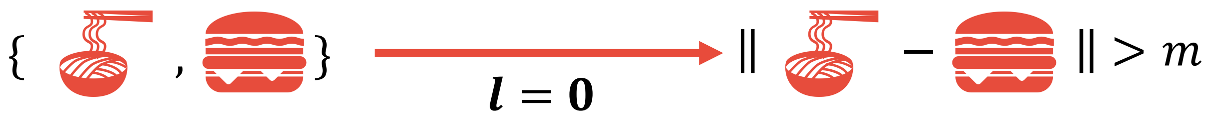
Food Similarity Embedding

Representation: 1000 dim visual + 200 dim ingredients

1000 dim visual feature from *Food-CNN*

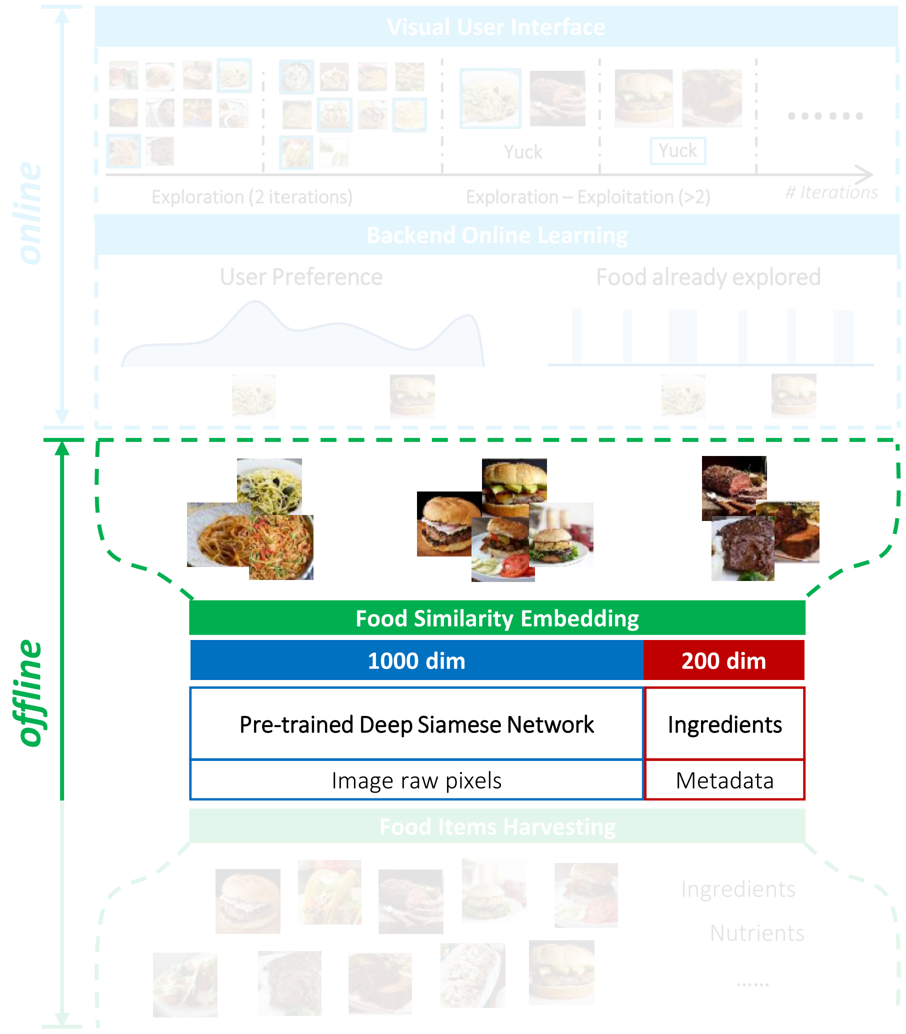


$$\mathcal{L} = \frac{1}{2} l D^2 + \frac{1}{2}(1 - l)\max(0, m - D)^2$$



Pairs/Labels were sampled from Food-101 dataset

System Design: *offline*



Food Similarity Embedding

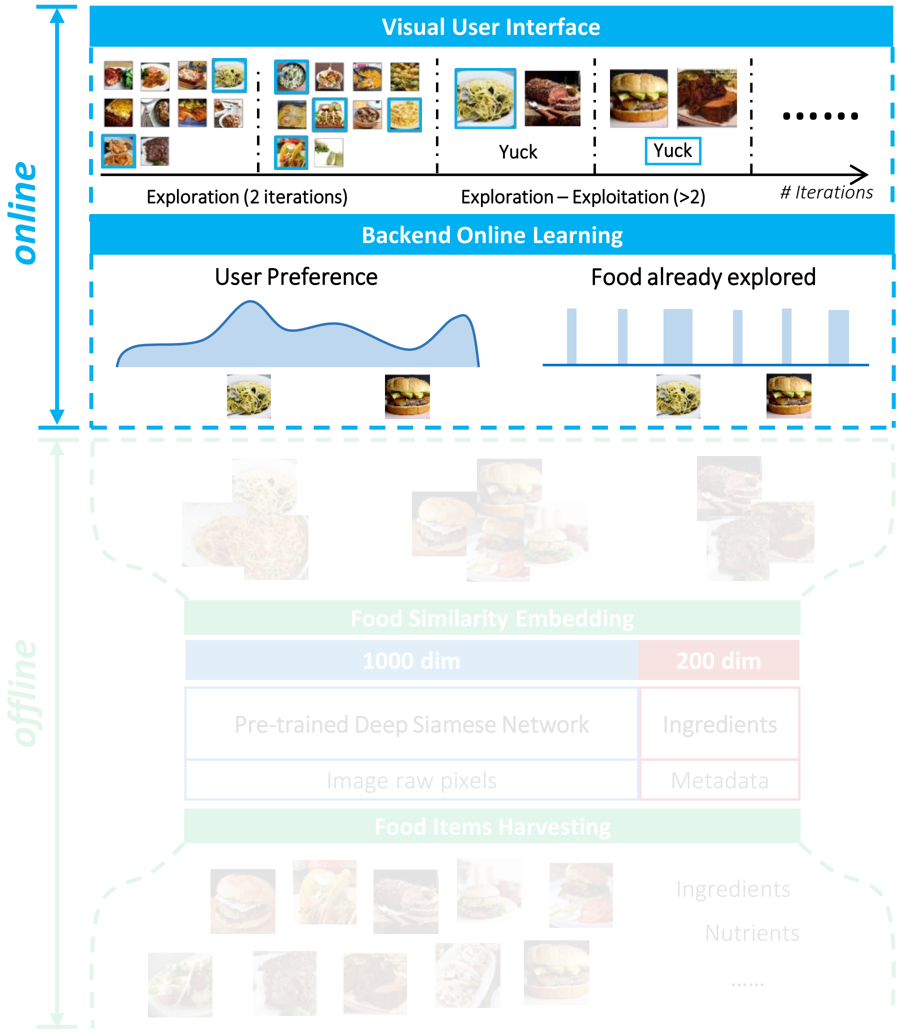
Representation: **1000 dim visual** + **200 dim ingredients**

200 dim ingredients feature

- **Lemmatization and preprocessing.**
- **Filtering:** Top 200 ingredients.
- **Feature vector:** 0-1 vector denotes the existence of the ingredient.

Visual and **ingredients** feature vectors are normalized separately with l_1 **norm**

System Design: *online*



Online Learning

Food preferences representation:

$$\boldsymbol{p}^t = [p_0^t, p_1^t, \dots, p_{|\mathcal{S}|}^t] \quad \sum_i p_i^t = 1$$

Distribution of preferences over all food items in $\mathcal{S}$

$\boldsymbol{p}^t$:updated preference vector after *iteration t*

Two tasks at each ***iteration t:***

- **User state update:** update $\boldsymbol{p}^t$ based on the items presented and user's choices at *iteration t-1*.
- **Images selection:** Select a set of images to show at *iteration t*.

System Design: *online*

Online Learning

- **User state update:**

  update $\boldsymbol{p}^t$ based on the items presented and user's choices at ***iteration t−1***.

Users' selections	→	**Image Labeling**
Images selected	→	**Label "+1"**
Images not selected	→	**Label "−1"**
Images not presented	→	**Label "0"**

System Design: *online*

Online Learning

- **User state update:**

update $\boldsymbol{p}^t$ based on the items presented and user's choices at ***iteration t−1***.

Label propagation with regularized optimization

$$\min_{\boldsymbol{u}} \underbrace{\sum_{j=1, j\neq i}^{|\mathcal{S}|} \omega_{ij}\left(y_i - u_j\right)^2}_{\text{Smoothness}} + \underbrace{\sum_{j=1, j\neq i}^{|\mathcal{S}|} \left(1-\omega_{ij}\right)\left(u_j - y_j\right)^2}_{\text{Fitting}}$$

Label Propagation and ***E***xponentiated Gradient Algorithm (***LE***)

$$\omega_{ij} = e^{\frac{-1}{2\alpha^2}\left\|f^{s_i} - f^{s_j}\right\|} \qquad u_j = \sum_{i=1}^{|\mathcal{S}|} \omega_{ij} y_i \qquad p_i^t \longleftarrow p_i^{t-1} \times e^{\frac{\beta u_i^{t-1}}{p_i^{t-1}}}$$

System Design: *online*

Online Learning

- **Images selection:** Select a set of images to show at ***iteration t***.

*E*xploration and *E*xploration–exploitation Algorithm (***EE***)

Exploration (Ten images): $t \leq 2$

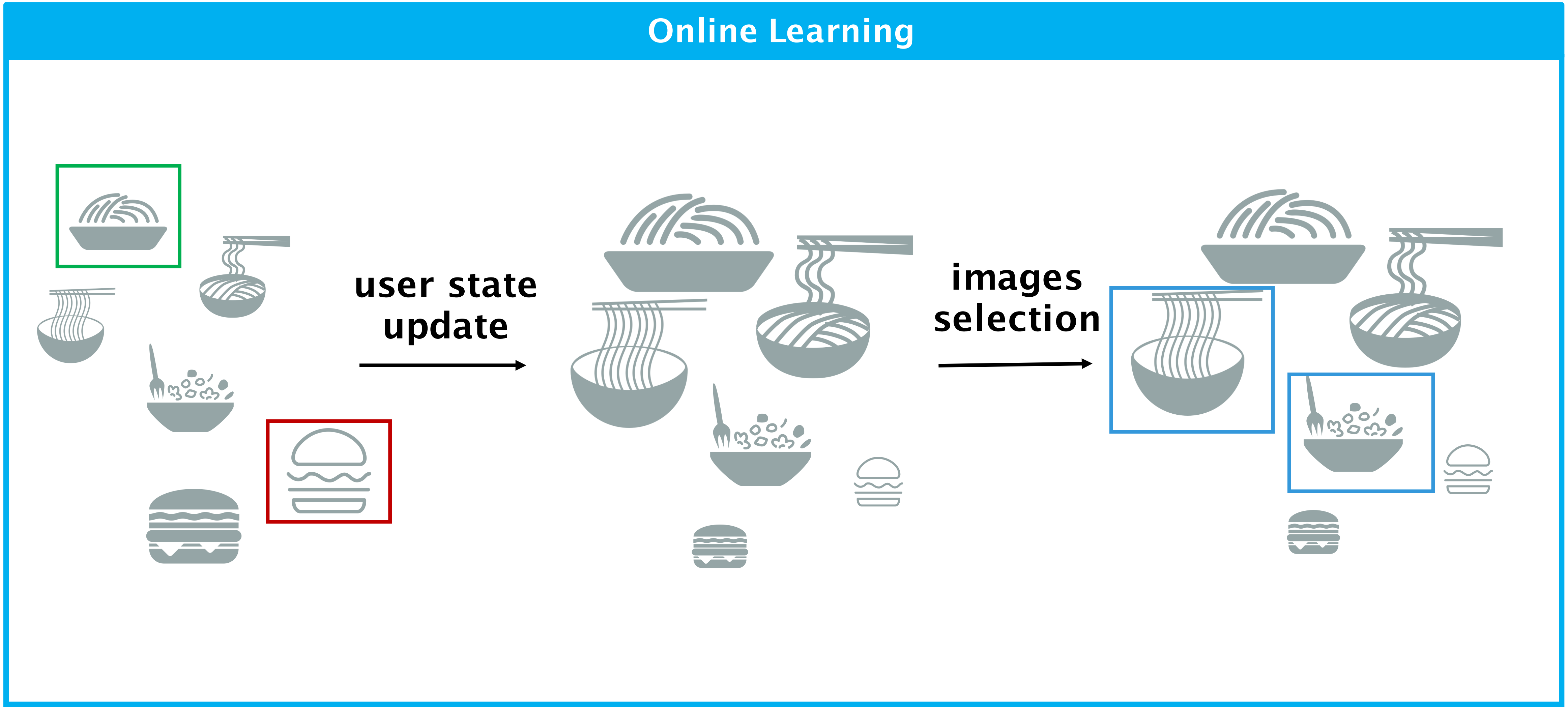
K–means++

Exploration–exploitation (Two images): $t > 2$

One Item that user "prefer" (with high value of p)

The other item that user hasn't explored.

System Design: *online*



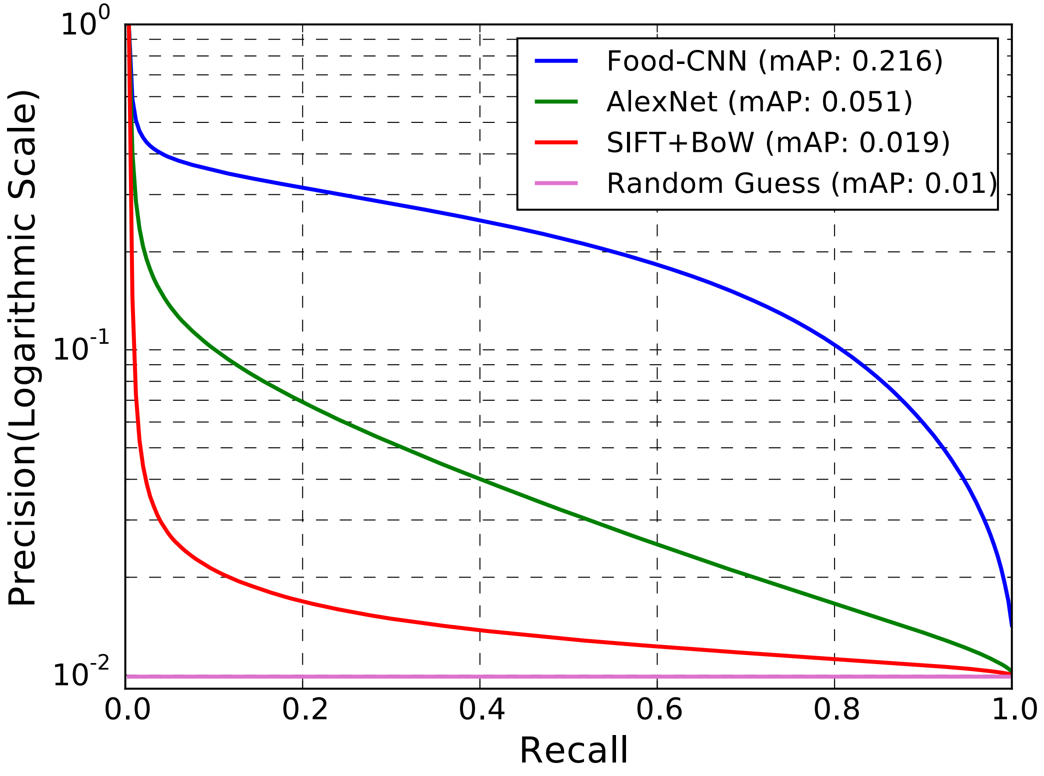
EXPERIMENTS AND USER STUDY

Evaluation, findings and evidence

Experiments: *embedding*

Clustering performance of *Food-CNN* (Tested on *Food-101 dataset*).

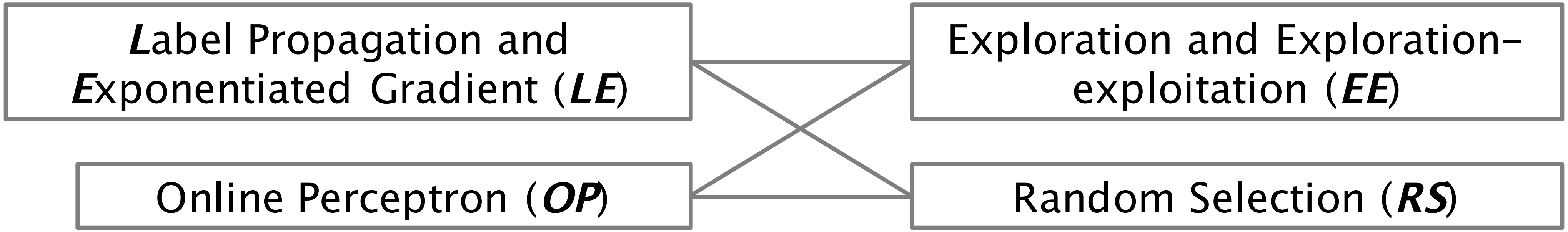
- ➢ ***K***-neighbors of each test image, calculate the precision-recall for each ***K***



Experiments: *user study*

- *227* anonymous users.
- Two factors were controlled in the study.

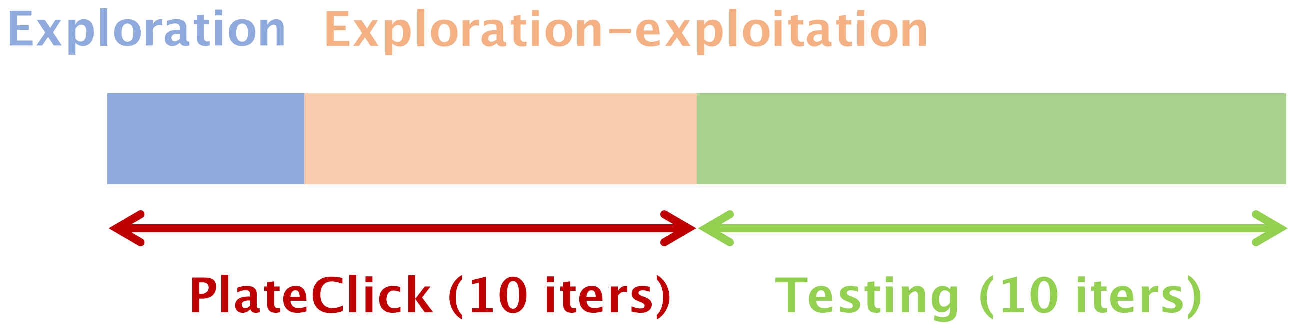
1st. Algorithm:



2nd. Number of iterations: 5/10/15

Experiments: *user study*

- Algorithm to test: ***LE+EE***
- Trials: ***1***/3

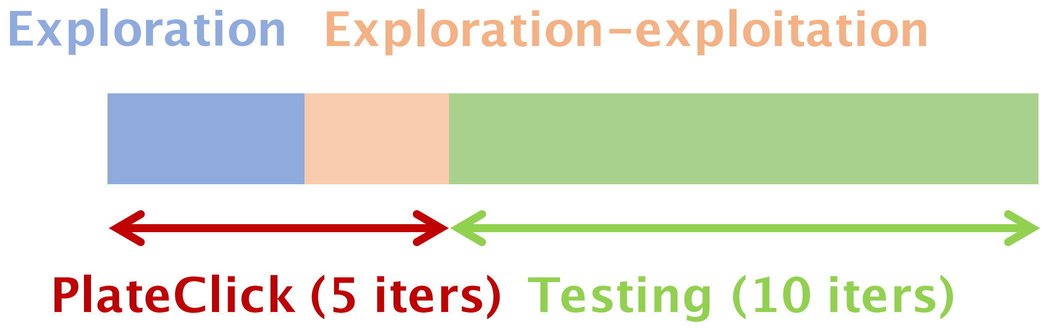


One image from top 1% of preference value. (***unexplored***)

The other image from bottom 1% of preference value. (***unexplored***)

Experiments: *user study*

- Algorithm to test: ***LE+EE***
- Trials: ***2***/3



One image from top 1% of preference value. (***unexplored***)

The other image from bottom 1% of preference value. (***unexplored***)

Experiments: *user study*

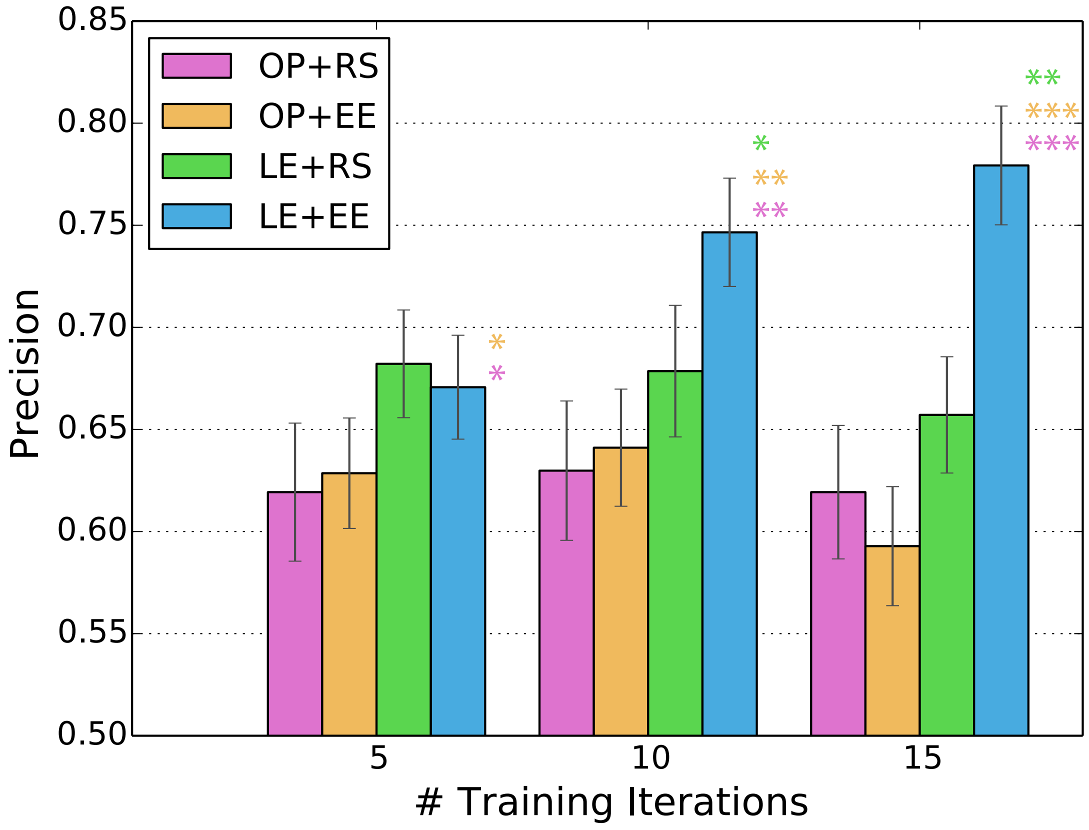
- Algorithm to test: ***LE+EE***
- Trials: ***3***/3

One image from top 1% of preference value. (***unexplored***)

The other image from bottom 1% of preference value. (***unexplored***)

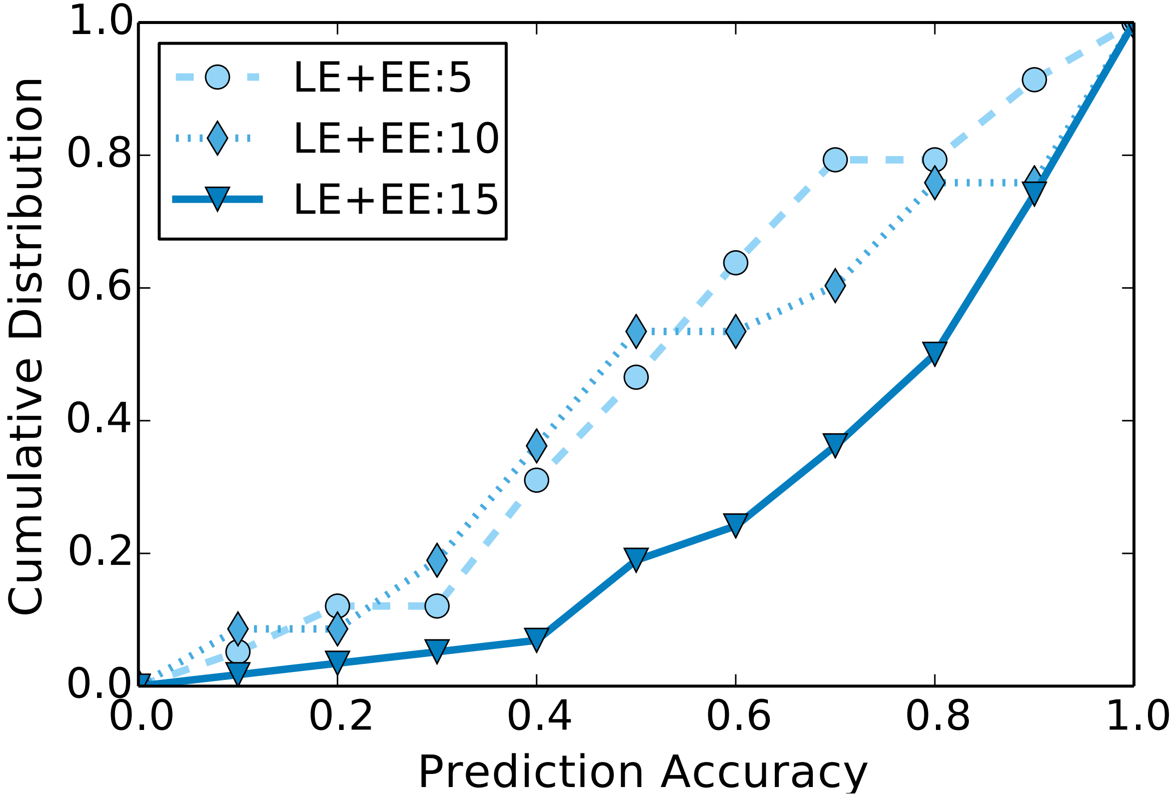
Experiments: *user study*

Prediction accuracy under different algorithms and number of iterations

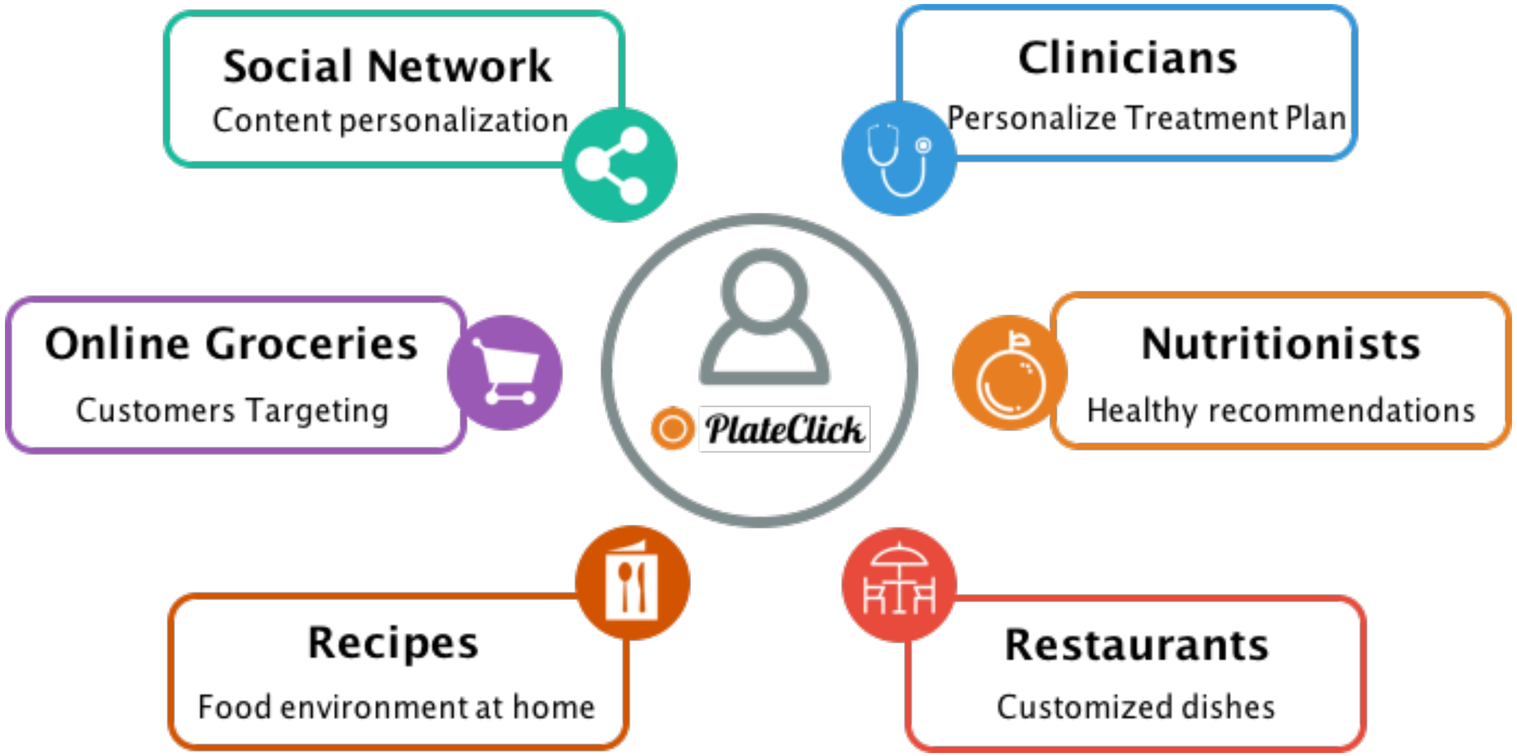


Experiments: *user study*

Cumulative distribution of prediction accuracy for LE+EE algorithm



Conclusions and Future work



- Engine for food preferences learning.
- Applicable to general human-in-the-loop problems.

For more information:

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Try it out online:

http://bit.ly/plateclick

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