

TECHFEST.PREFERRED.AI

23rd August 2019

Supported by:



Office of
Postgraduate Research
Programmes

School of
Information Systems

About Us

PREFERRED.AI is a research group at SMU School of Information Systems (SIS). In this TechFest, we will share recent projects that the group is actively pursuing.

Mission

Our mission is to “push the envelope” on learning user preferences from data to improve the effectiveness and efficiency of recommendations using data mining, machine learning, and artificial intelligence. This encompasses designing algorithms for mining user-generated data of various modalities (e.g., ratings, text, images, social networks) for understanding the behaviours and preferences of users (individually and collectively), and applying the mined knowledge to develop user-centric intelligent applications.

Programme

SESSION I – TALKS (3.30PM to 5.00PM)

SMU School of Information Systems, Seminar Room B1-1

-  **Preferred.AI:** Preferences and Recommendations from Data & AI
 - an overview of our activities and how you can get involved
-  **PCRL:** Jointly Modeling User Preferences and Learning Deep Item Features from Auxiliary Data
 - a publication at The Conference on Uncertainty in Artificial Intelligence (**UAI-18**)
-  **MRG:** Multimodal Review Generation for Recommender Systems
 - a publication at The Web Conference (**WWW-19**)
-  **CompareLDA:** A Topic Model for Document Comparison
 - a publication at The AAAI Conference on Artificial Intelligence (**AAAI-19**)
-  **MP-SimRank:** Multiperspective Graph-theoretic Similarity Measure
 - a publication at The ACM Conference on Information and Knowledge Management (**CIKM-18**)

SESSION II – POSTERS AND DEMOS (5.00PM to 6.30PM)

SMU School of Information Systems, Concourse opposite OCBC

- **Cerebro:** Closed-loop recommendation retrieval engine
- **Cornac:** Multimodal recommender system library
- **JioApp:** Recommendations for group meetups
- **Propedia:** Web-mined product encyclopedia
- **SentiVec:** Sentiment-infused word embeddings
- **ThriftCity:** Web-sourced price comparisons
- **Venom:** Focused crawler for the deep Web
- **Butler:** Conversational recommender system with natural language explanations
- **FaceInMotion:** Face-based intelligent emotion detection
- **MindReader:** News recommendation app based on reading history
- **Neural Network Lab:** Machine learning in your browser

PCRL: Jointly Modeling User Preferences and Learning Deep Item Features from Auxiliary Data

<https://cornac.preferred.ai>

Personalized recommendation

	5	3	?	?
	?	?	2	?
	?	?	5	4

Preference data: user-item interactions
e.g., **clicks, ratings, purchases**

Objective

- ▶ Predict unknown user-item interactions.

Challenge

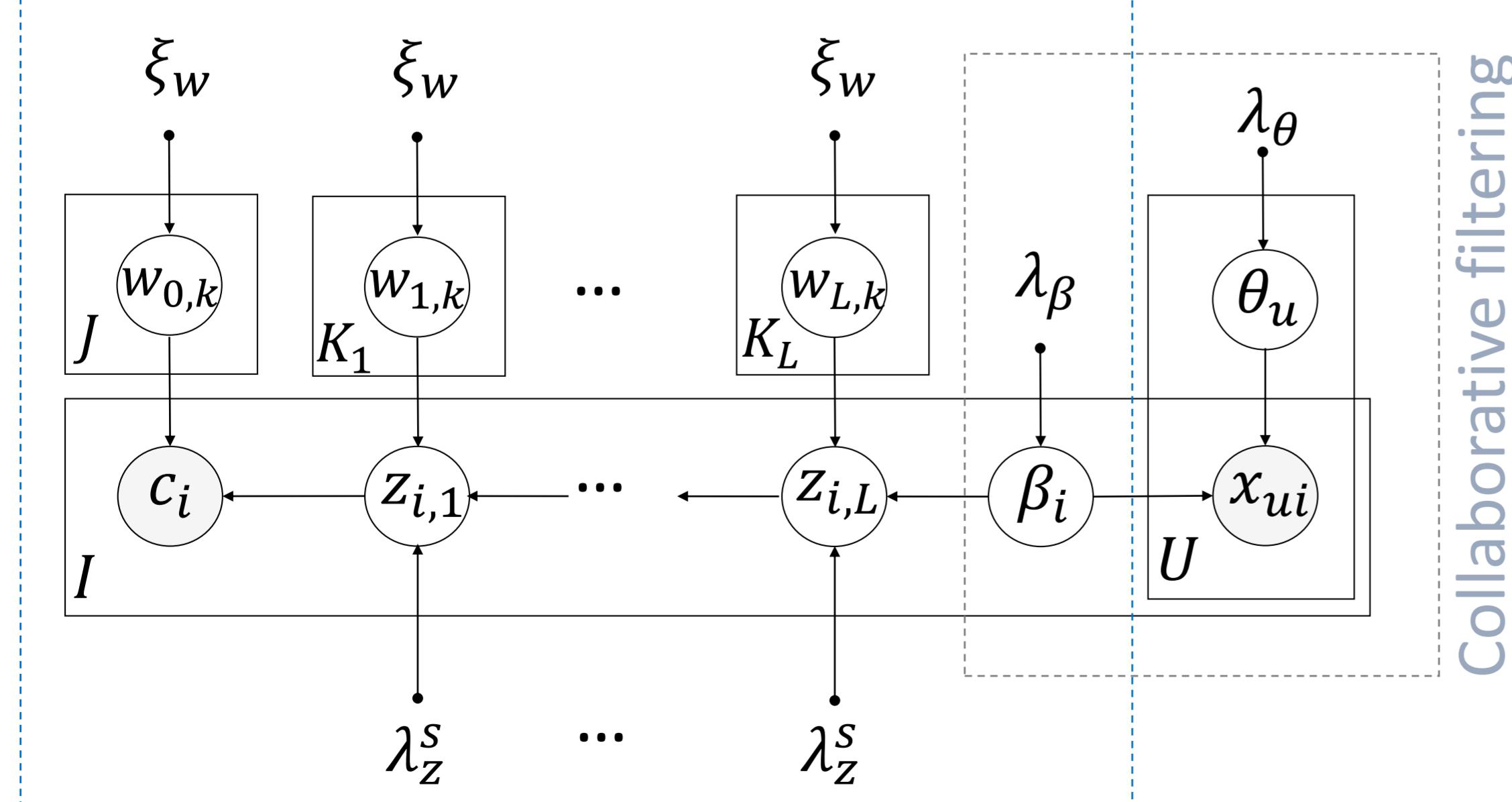
- ▶ Data is extremely sparse
- ▶ Do not cover all aspects of user behavior
- ▶ Difficult to generalize a user's preference

Personalized recommendation



PCRL: putting it all together

Deep item representation



PCRL's graphical model

Intuition

- ▶ Preferences guide representation learning
- ▶ Content helps in predicting preferences

MGR: Multimodal Review Generation for Recommender Systems

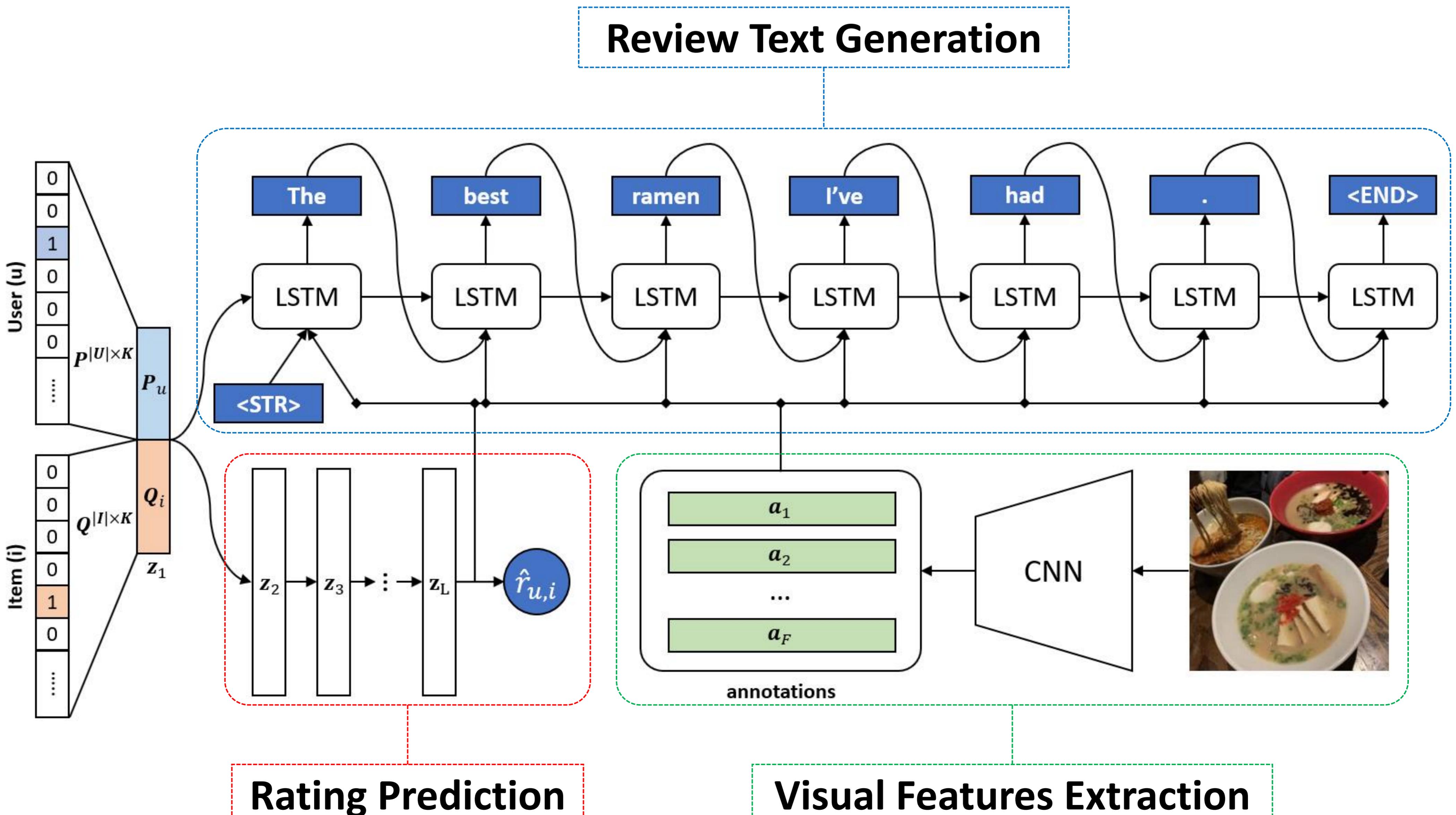
<https://code.preferred.ai/mrg>

Problem



- Given:
 - a user
 - an item
 - an image (*optional*)
- Output:
 - rating (for *recommendation*)
 - review text (potentially for *explanation*)

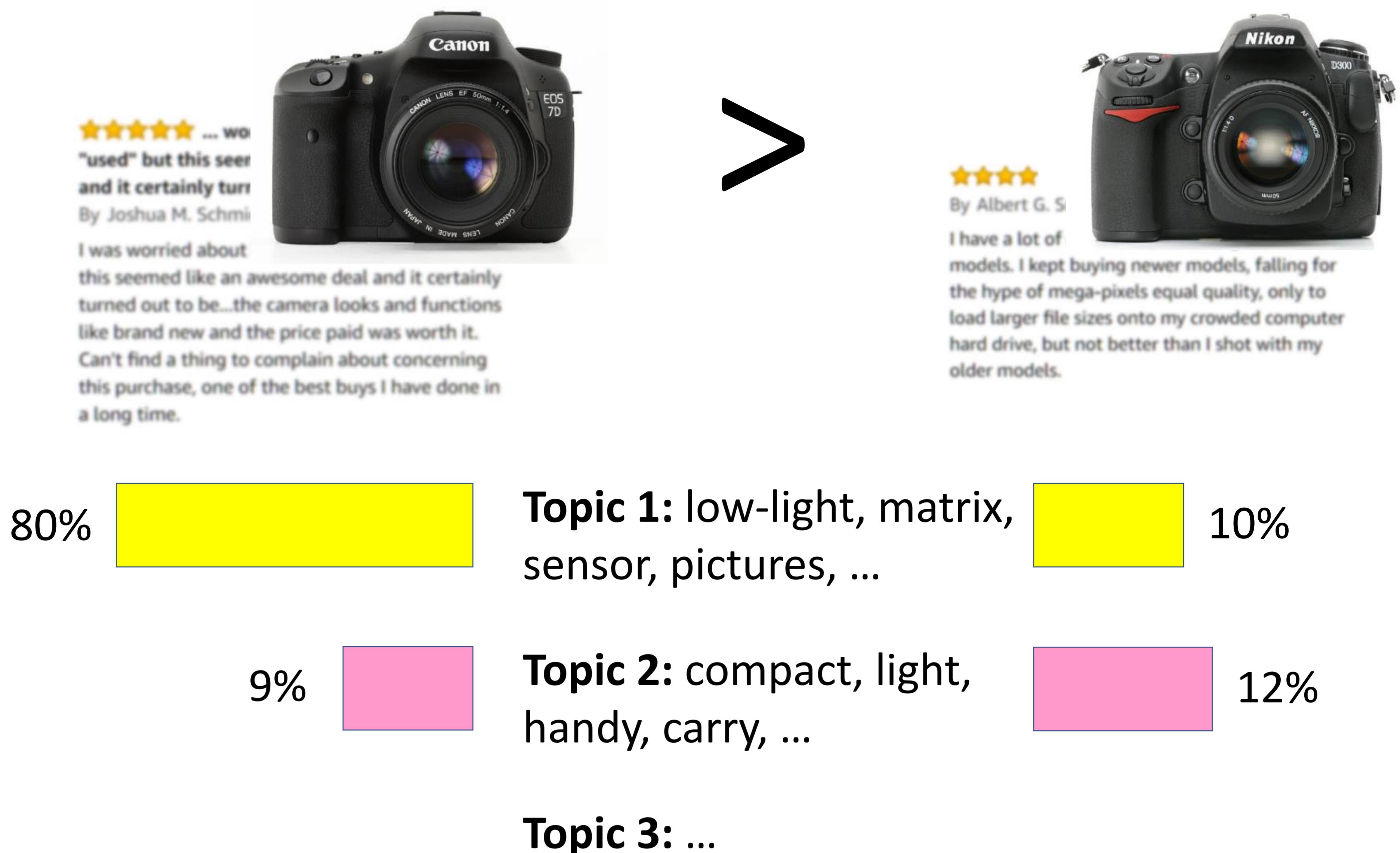
Multimodal Review Generation



CompareLDA: A Topic Model for Document Classification

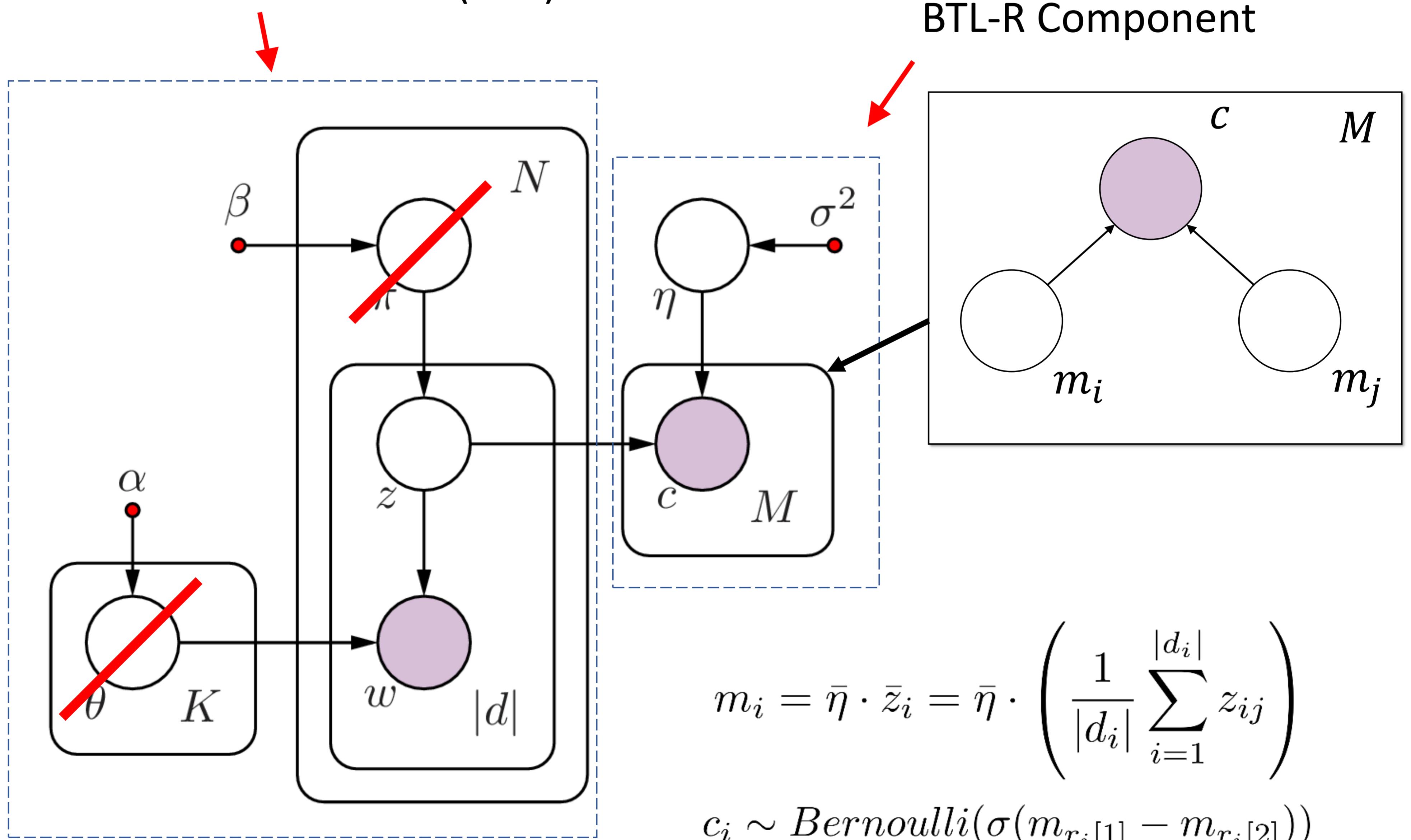
<https://code.preferred.ai/Compare-LDA>

Product Comparison



Multimodal Review Generation

Latent Dirichlet Allocation (LDA)



MP-SimRank: Multiperspective Graph-Theoretic Similarity Measure

<https://code.preferred.ai/mp-simrank>

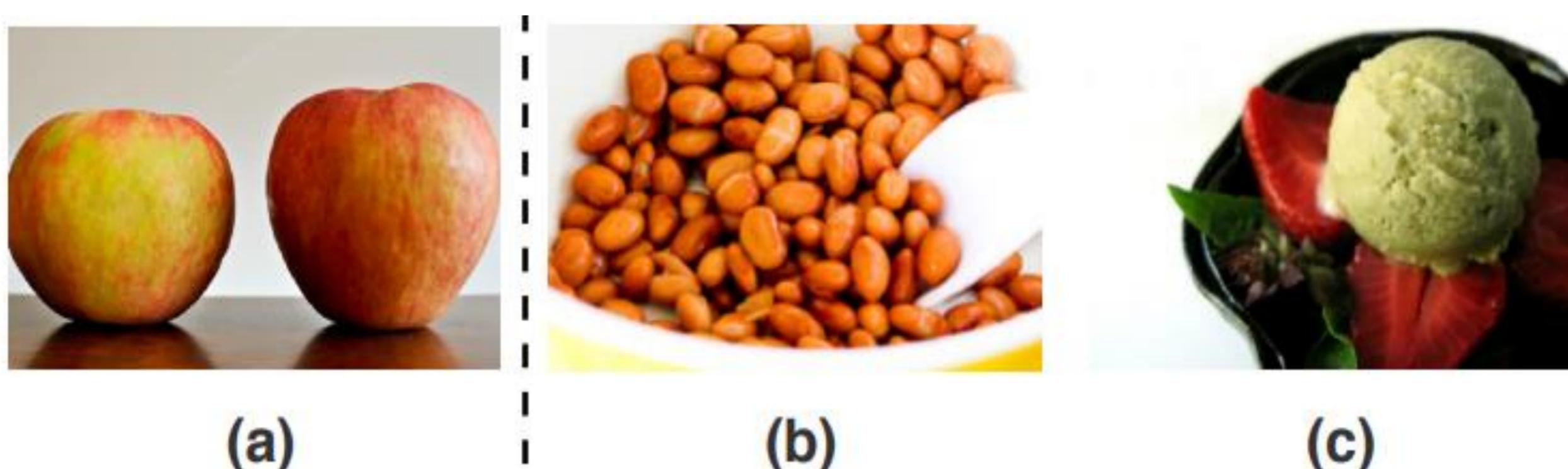
Questions

How to tell when two objects are similar?

According to what perspective?

Challenges

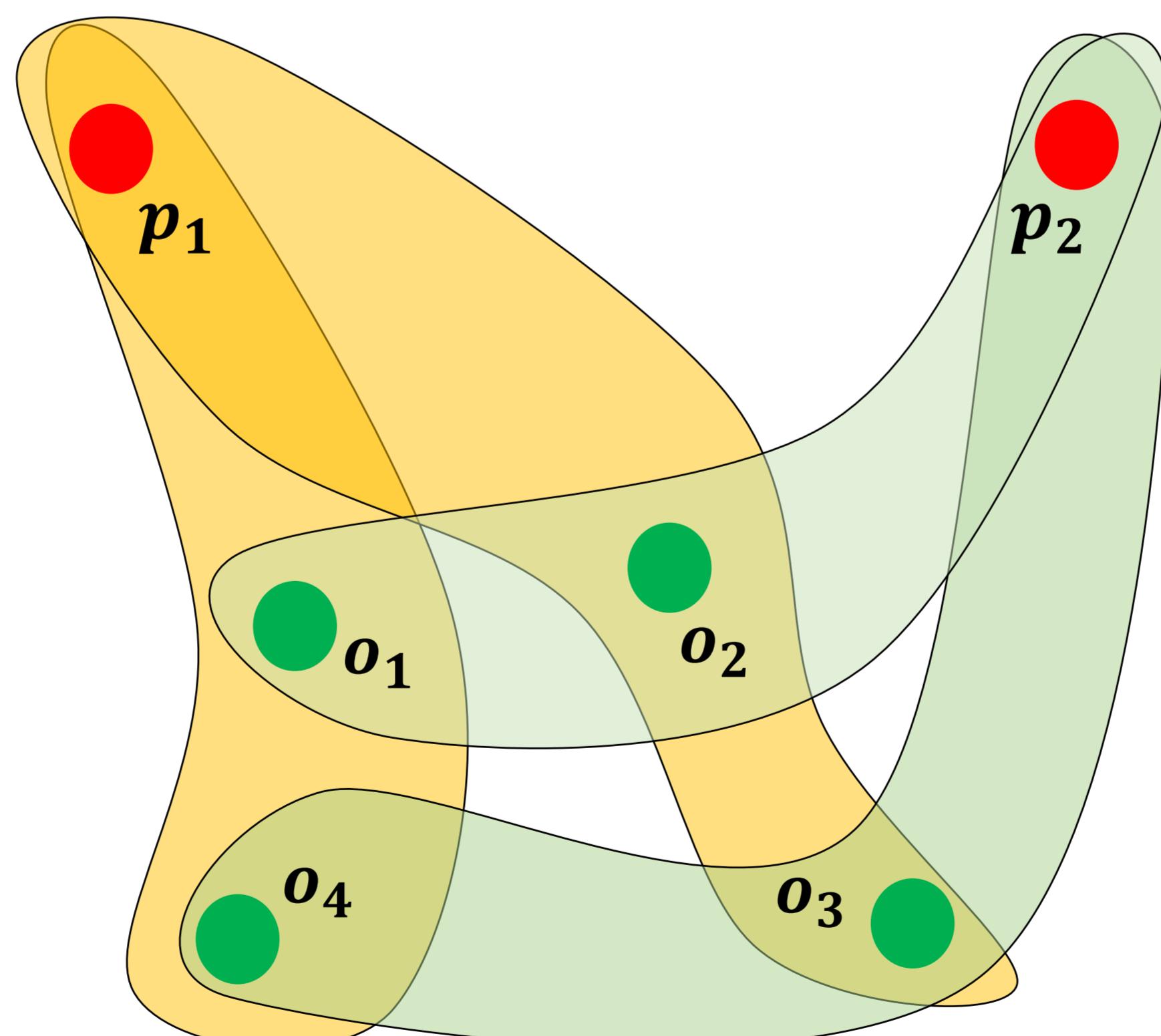
- ❑ Similarity observations for each perspective might be under-sampled, do not cover all objects.
 - ❑ Two objects are similar according to one perspective, but not to the other.



Which picture is more similar to picture (a)?
(b) or (c)?

Multiperspective Similarity Measure

$$S_p^{(t+1)}(o_i, o_j) = \frac{C}{|P|} \sum_{p^* \in P} \text{sim}^{(t)}(p, p^*) \times \sum_{o_k \in N_{p^*}(o_i)} \sum_{o_l \in N_{p^*}(o_j)} \frac{S_{p^*}^{(t)}(o_k, o_l)}{|N_{p^*}(o_i)| |N_{p^*}(o_j)|}$$



Base cases:

$$\begin{cases} \mathbf{sim}^{(0)}(p, p^*) = 1 \text{ if } p = p^* \text{ and } 0 \text{ otherwise} \\ S_p^{(0)}(o_i, o_j) = 1 \text{ if } i = j, \forall p \text{ and } 0 \text{ otherwise} \end{cases}$$

Need to measure: $\text{sim}(p, p^*)$ and $S_p(o_i, o_j)$

Closed-Loop Recommendation Retrieval Engine

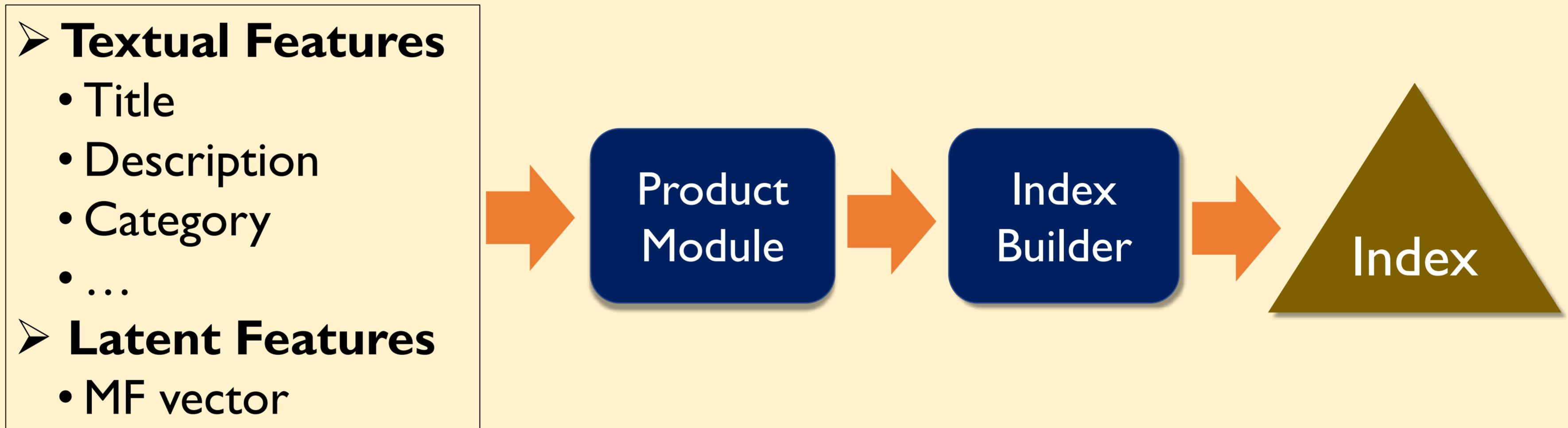


Fast Retrieval

Implementing indexing structures to support various types of information retrieval, e.g., personalized recommendation, personalized keyword search, and similar products search.



Cornac

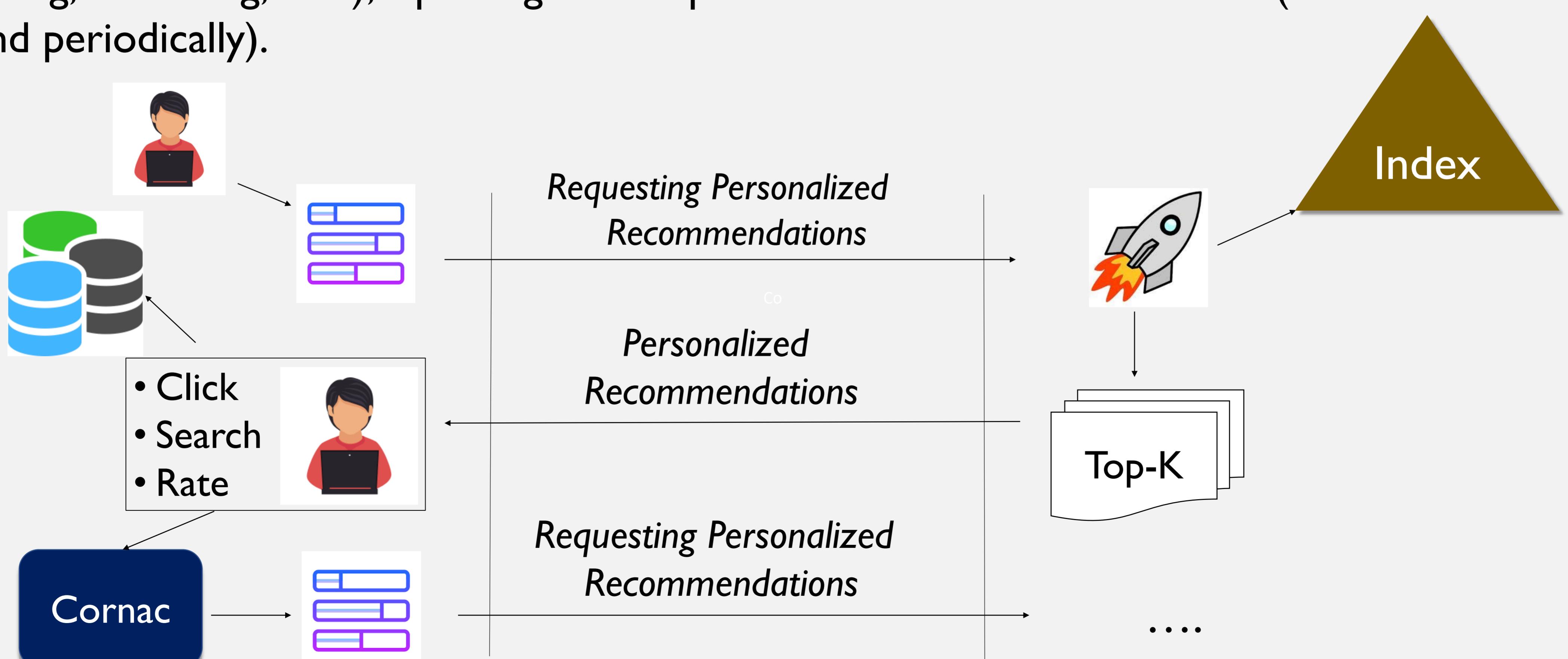


<https://cornac.preferred.ai/>

Sub-linear Time Retrieval via Indexing

Recommendation Framework

Initiating and managing recommendation session, tracking users' actions (e.g., clicking, rating, searching, etc.), updating users' personalized recommendations (within session and periodically).

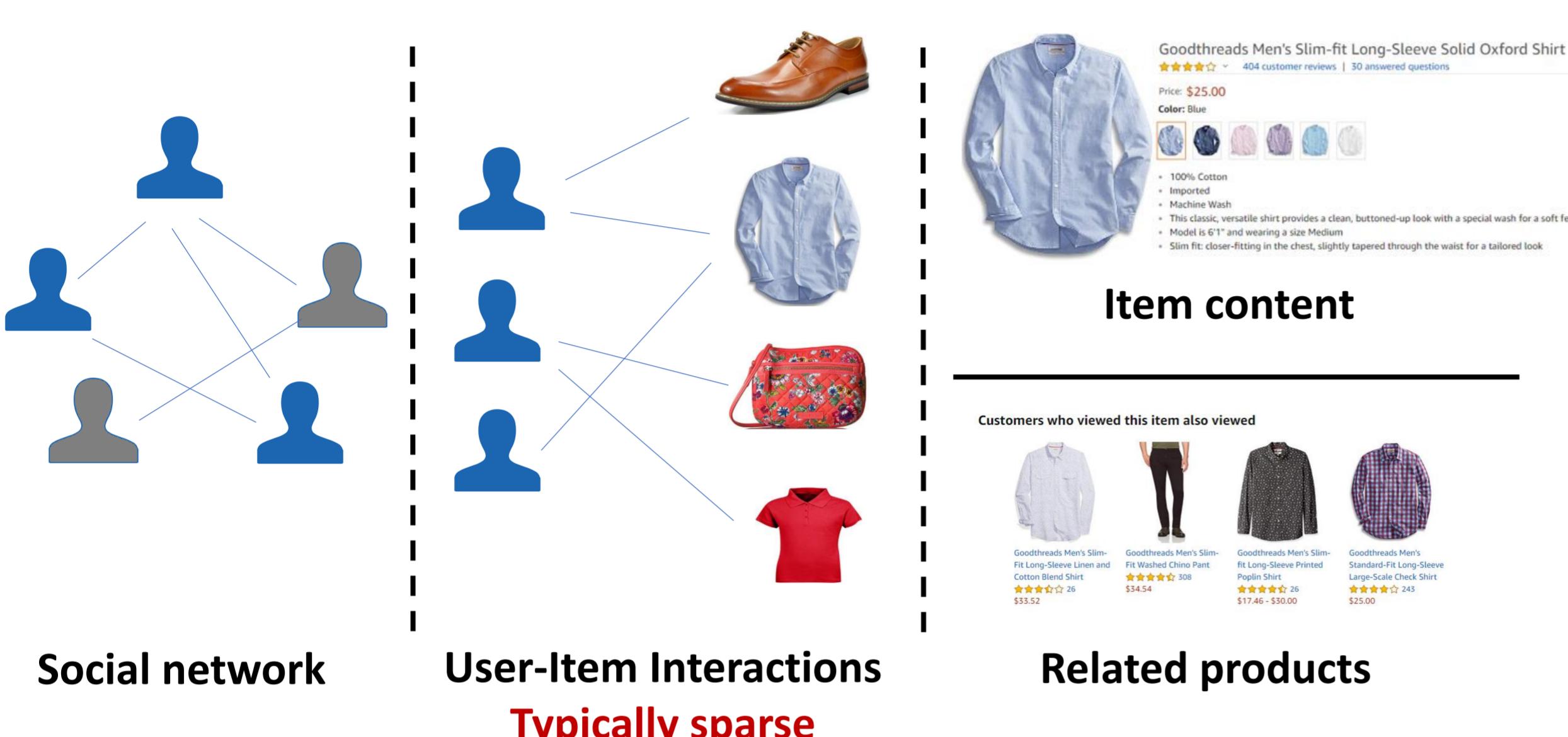


<https://cornac.preferred.ai/>

Closed-loop and End-to-end

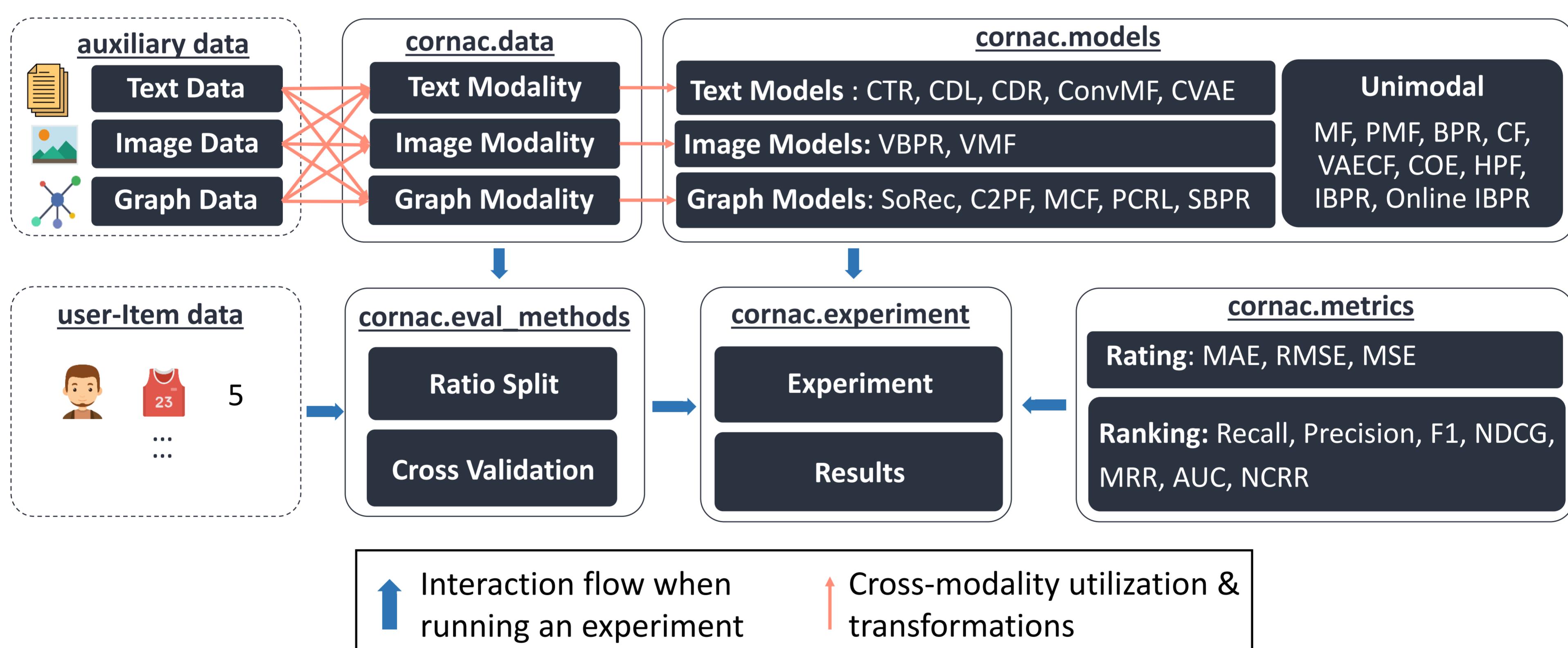
A Library for Multimodal Recommender System

- *Multimodal Recommender Systems leverage auxiliary information to alleviate data sparsity*



- Fast experimentation, exploration, and comparisons
- Convenient development of new multimodal recommenders
- Open-access to a rich collection of recommendation models
- Straightforward usage of real-world benchmark datasets

Structures



Key Features

- **Multimodality.** Data infrastructures make it convenient to work with auxiliary information and enable seamless cross-modality comparisons.
- **Scalability.** A rich collection of iterators for easy stochastic optimization. Model implementations make use of Cython to achieve C/C++ performance.
- **Reproducibility.** Full control over random number generators, open-access to existing algorithms and built-in datasets for reproducible research.

Food Recommendations for Group Meetups

- Personalised group-based food recommendations application
- Aggregates food preferences of users in a group
- Provides list of food establishments based on the overall preference of the group

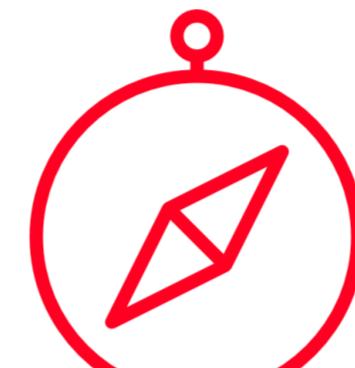
Why JioApp?



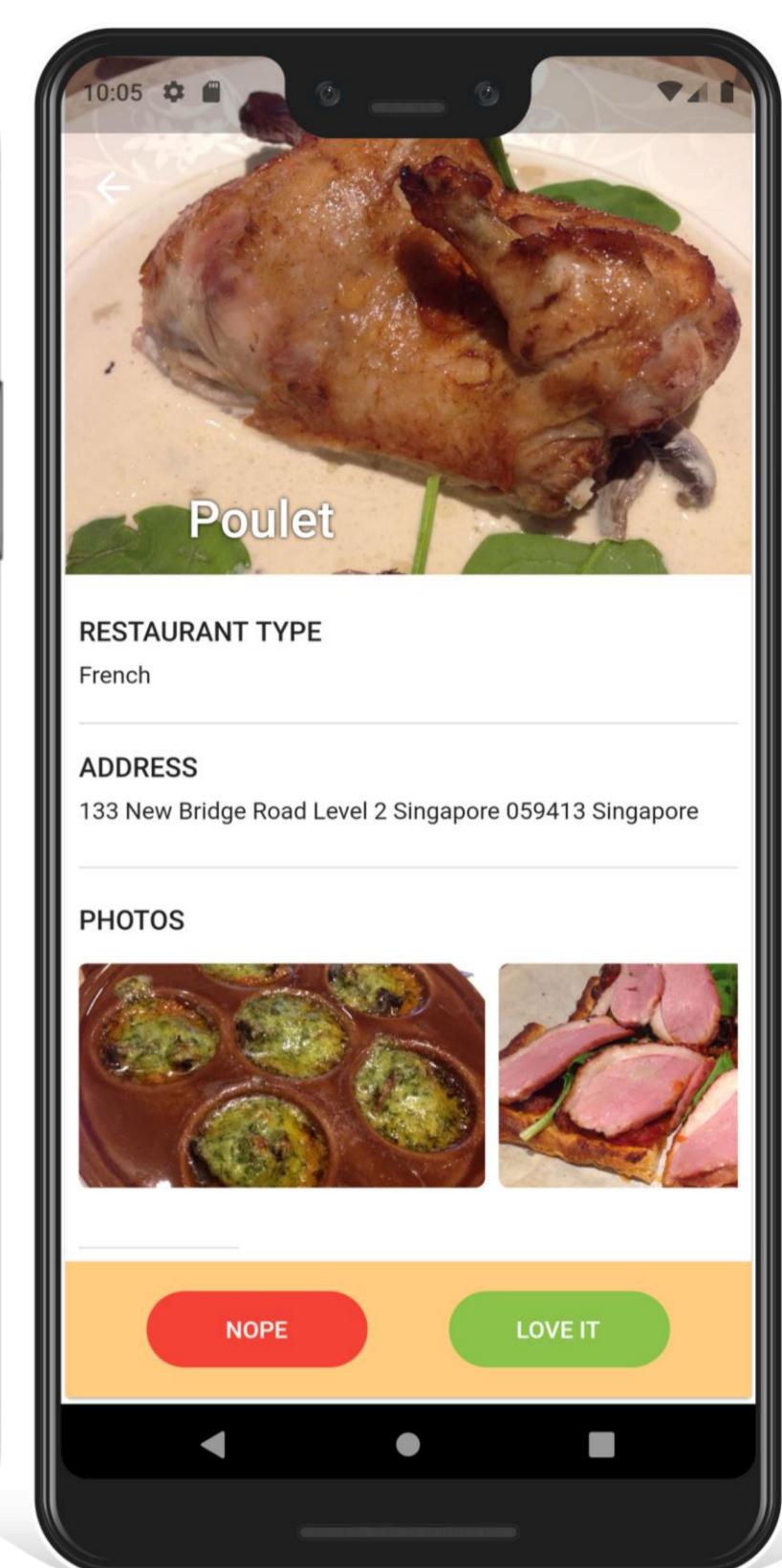
Ease of planning group meetups



Know everyone's food preferences



Find a food place that most group members likes



Download on the
App Store

GET IT ON
Google Play

Key Features



EASY ACCESS TO FOOD OPTIONS

More than
7000 food establishments
over 26 Singapore regions



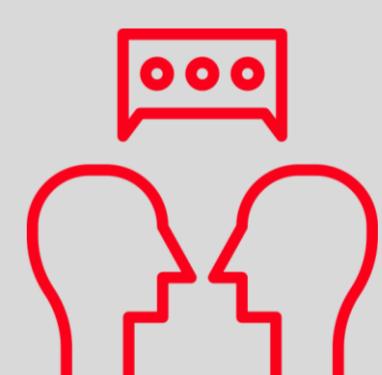
SIMPLE EVENT CREATION

Create events by selecting
attendees from your
contact list



SWIPE TO YOUR DESIRES

Swipe your screen to have
your preferences recorded



FEWER DECISIONS, MORE INTERACTION

Our machine learning
algorithm recommends the
best locations for your
group

Providing Recommendations

MOBILE APP

Android iOS

1
Create group event

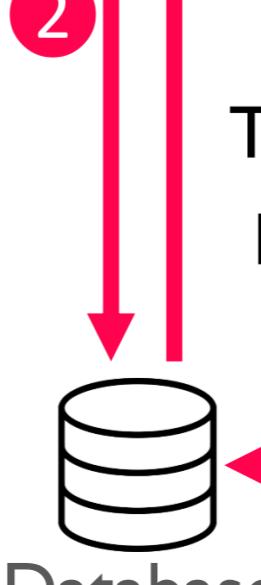
BACKEND

2
Users add preferences



Server

1
2



Database

The recommendation server learns
what a user likes based on their
preferences added

3

Using historical behavioural
data from all users

3

CORNAC
(<https://cornac.preferred.ai>)
Recommendation
Server

4

The recommendation server aggregates
preferences from users in a group and
provides recommendations

3

Web-Mined Product Encyclopedia

Multi-Source

Comprehensive catalogue integrated from different e-commerce platforms

amazon.com

淘宝网
Taobao.com

Lazada

亚马逊
amazon.cn

Multi-Lingual

Ease of accessibility to product information mined from different languages

中文 | English



PROPEDIA

Up-to-Date

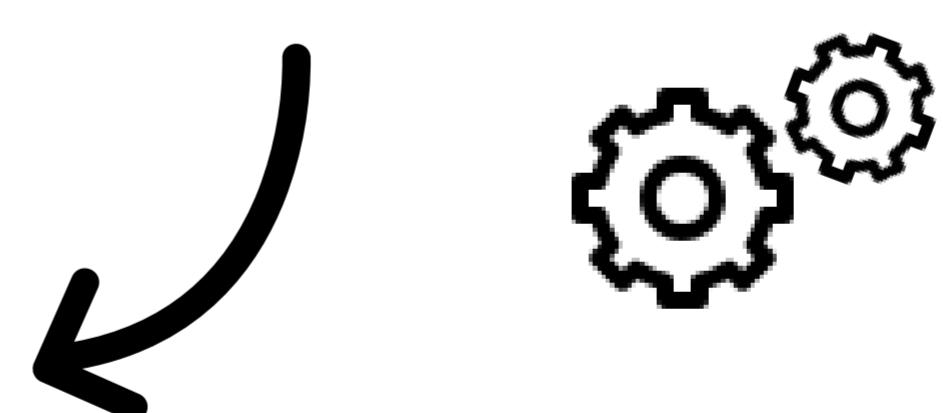
Continual data collection using Venom crawler (<https://venom.preferred.ai>)

Feed 1: BERT
Sentiment Analysis

P 96. / R 97.
F1 96.

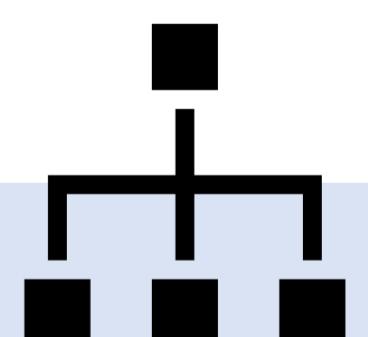
Feed 2: LingPipe
Sentiment Analysis

P 96. / R 90.
F1 93.

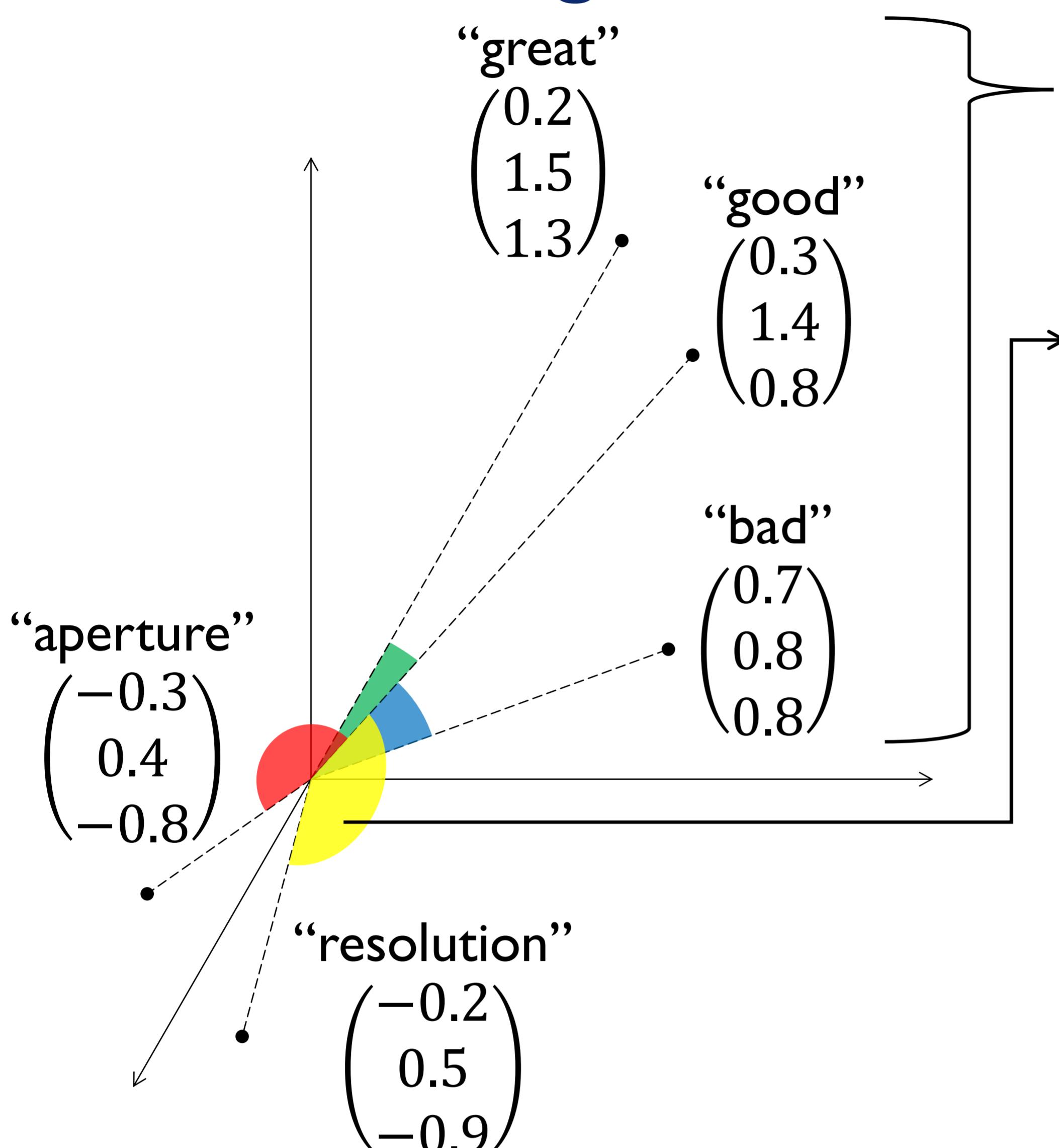


Multi-Feed

Parallel versions of product information reflecting diverse viewpoints and methodologies



Word Embeddings



Words with similar neighbours should have similar embeddings

Similarity is given by the angle between two embeddings

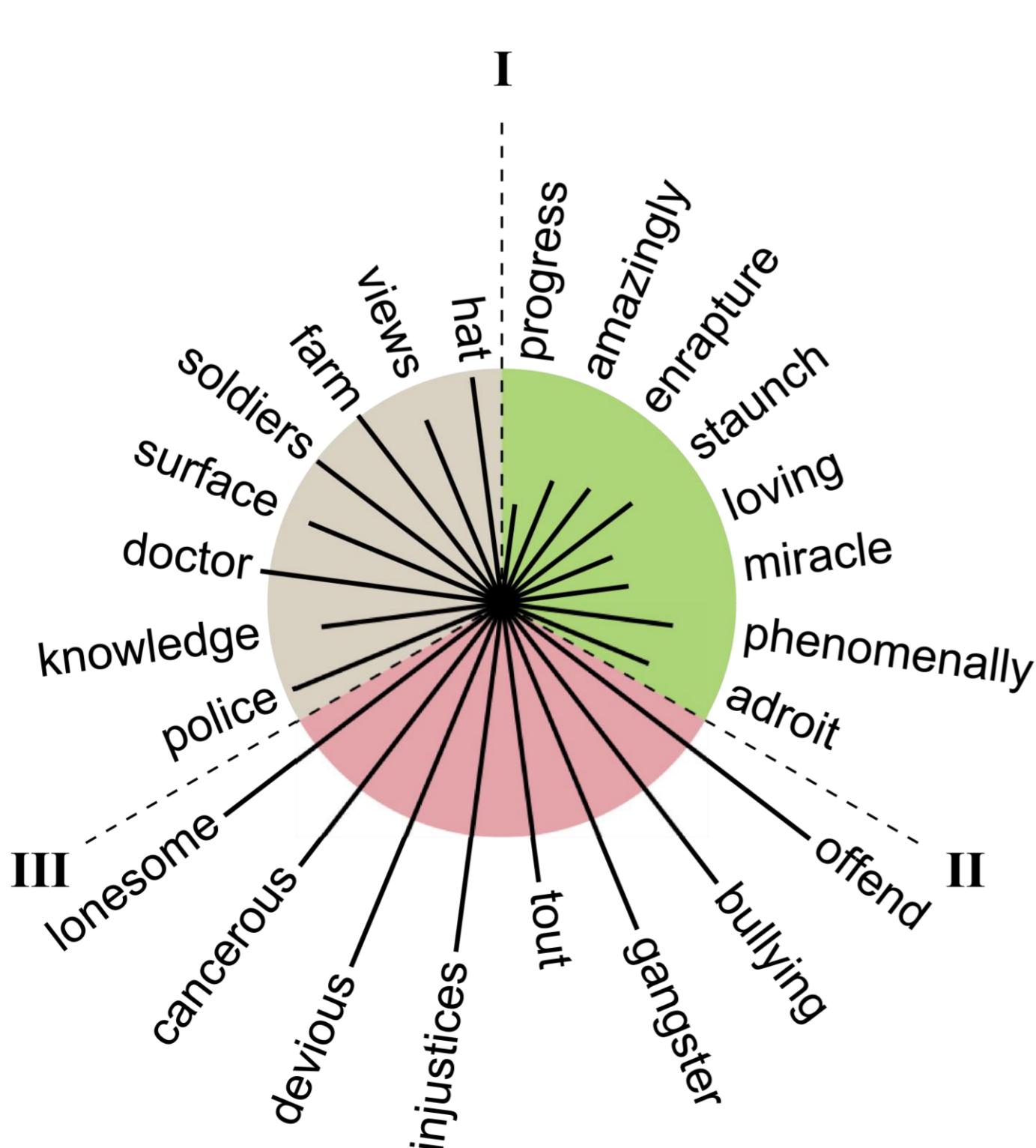
Applications

- Used in text classification tasks, such as sentiment analysis
 - Customer Profiling
 - Market Segmentation
- Typically obtained from distributional analysis methods e.g., Word2Vec

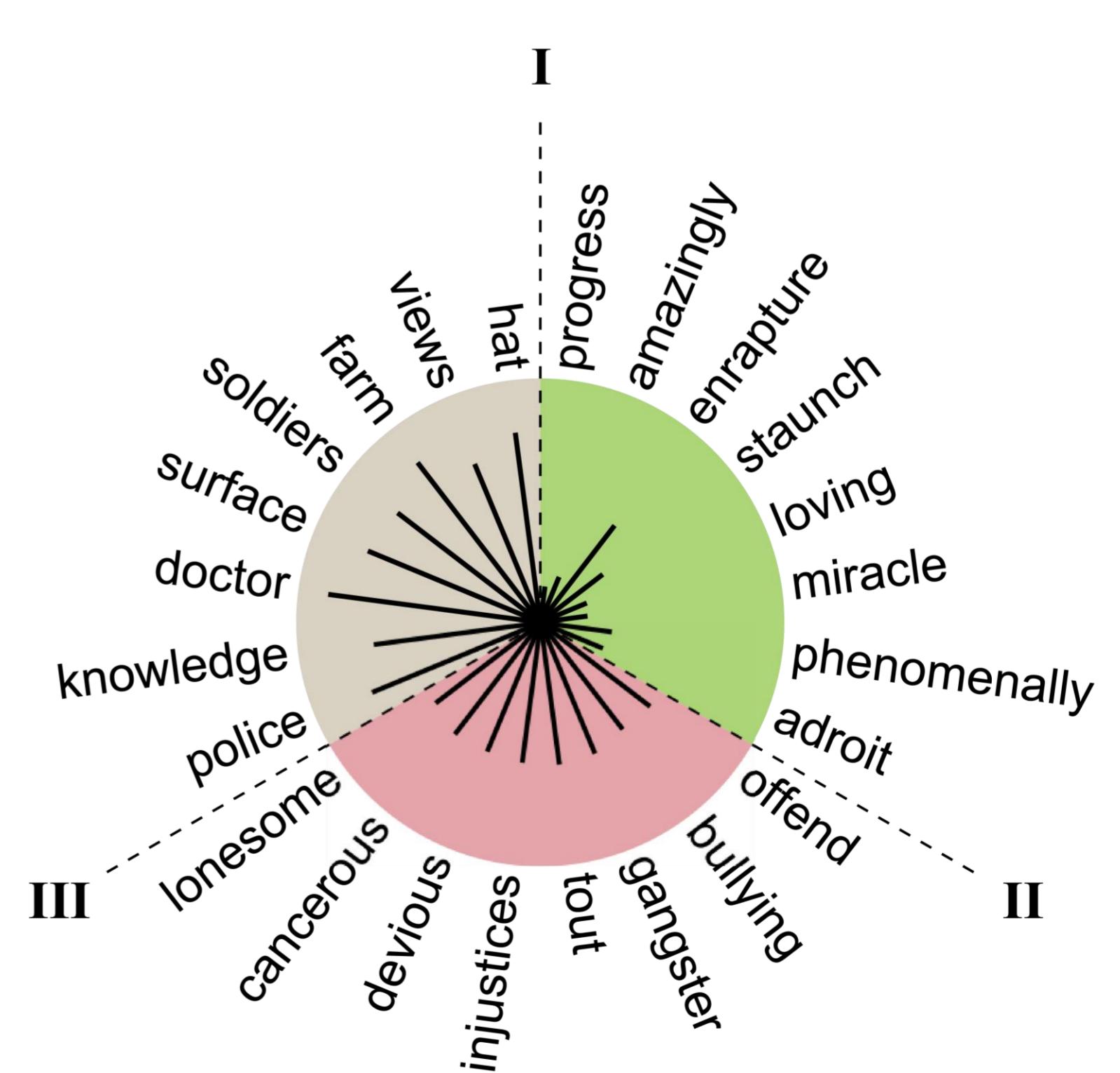
SentiVec: Sentiment-Infused Word Embeddings

-  Sentiment words (i.e. good, bad) have similar neighbours
 -  Incorporate alignment of words to sentiment, from external lexicon L
- $$\log \mathcal{L}_{\text{sentivec}} = \log \mathcal{L}_{\text{word2vec}}(W; C) + \lambda \log \mathcal{L}_{\text{sentiment}}(W, L)$$

-  Up to 85.7% accuracy for sentiment classification, higher than Word2Vec



Target word: "good"



Target word: "evil"

Relative changes in vector similarity, contrasted with Word2Vec



Getting the best prices from retailers worldwide is just a **click away**



Wide Variety

Search a unified catalogue of products, integrated from multiple retailers using Propedia (<https://propedia.preferred.ai>). Bringing to you all your favourite products on one platform.



Fast and Convenient

Check the reviews as well as the latest prices with shipping and taxes included. Bringing to you comprehensive information about products.



Enjoy Savings \$

Compare prices all-in between multiple retailers for the same product in your preferred currency. Linking you to retailers with the best offers.



Tailored for You, to You

ThriftCity remembers your preferences and fetches the most relevant products for you using Cerebro (<https://cerebro.preferred.ai>), a closed-loop recommendation retrieval engine.



Personalised
Homepage

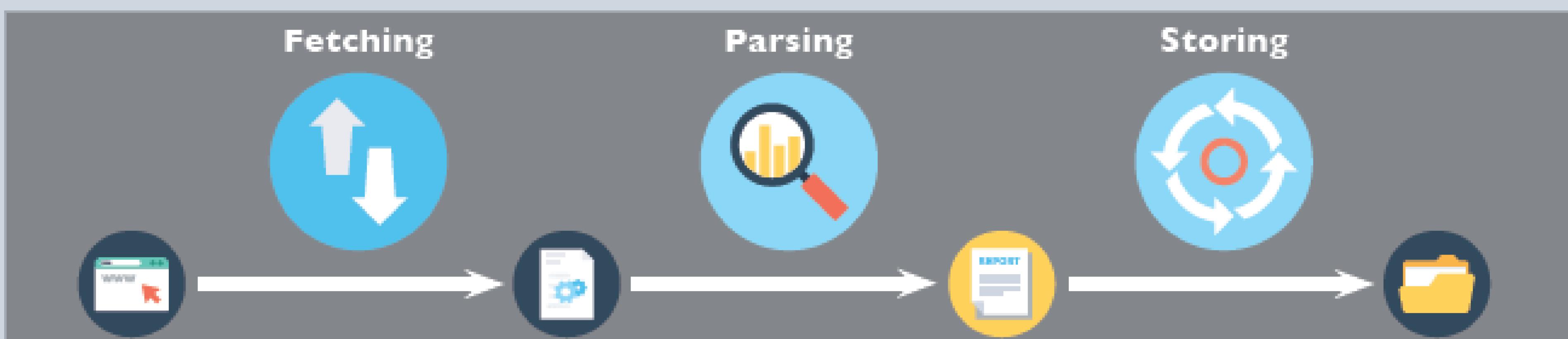


Personalised
Search



Personalised
Related Products

Your preferred open source focused crawler for the deep Web



Venom is a feature-packed crawling framework built with essential Web scraping features that are seamlessly integrated with content parsing and storage. Easy to use in both prototyping and production, it is available on all operating systems that support JAVA.



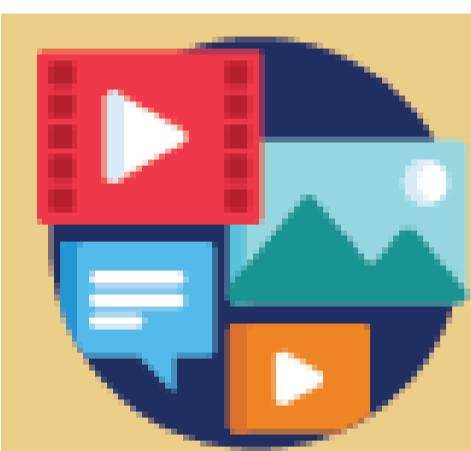
Blazing Fast Performance

Leverages an asynchronous, event driven I/O model, that can send and process massive number of requests while parsing and indexing massive amount of data with built-in multithreading.



Fully Customisable

Combines high-level API with low-level fine tuning, providing different users with the right amount of control they need over their crawlers.



Highly Robust

Handles issues gracefully with built-in header and content validation, which ensures data correctness through auto re-fetching. Fully integrated into the request-handler scheme.



Simple and Handy to Use

Provides all the essential features required to scrape the web, allowing you to write a full-fledged crawler in just a few lines of code. We do all the work so you don't have to.

Notable features



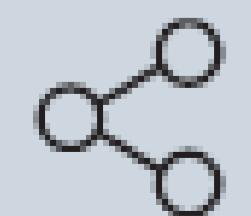
Structured crawling with jsoup integration



Page validation and retry handling



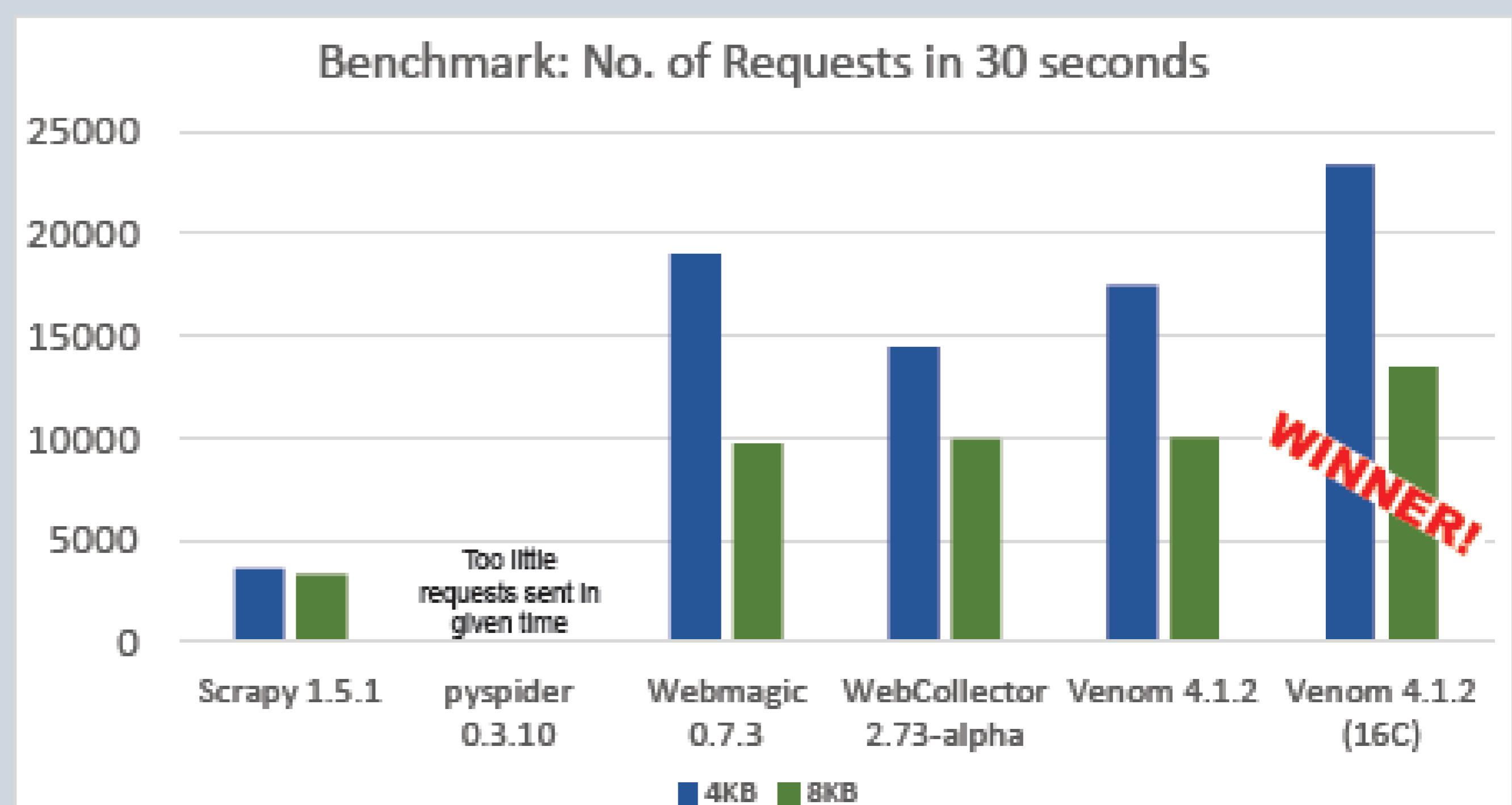
Built-in raw file storage system and reparsing

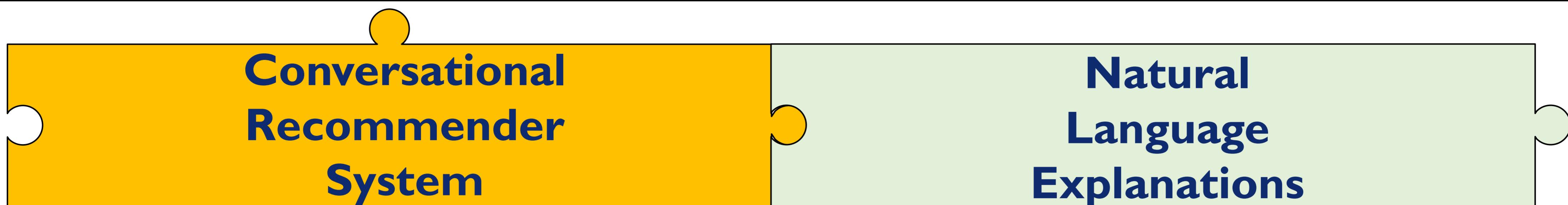


Proxy support



Open source and free!





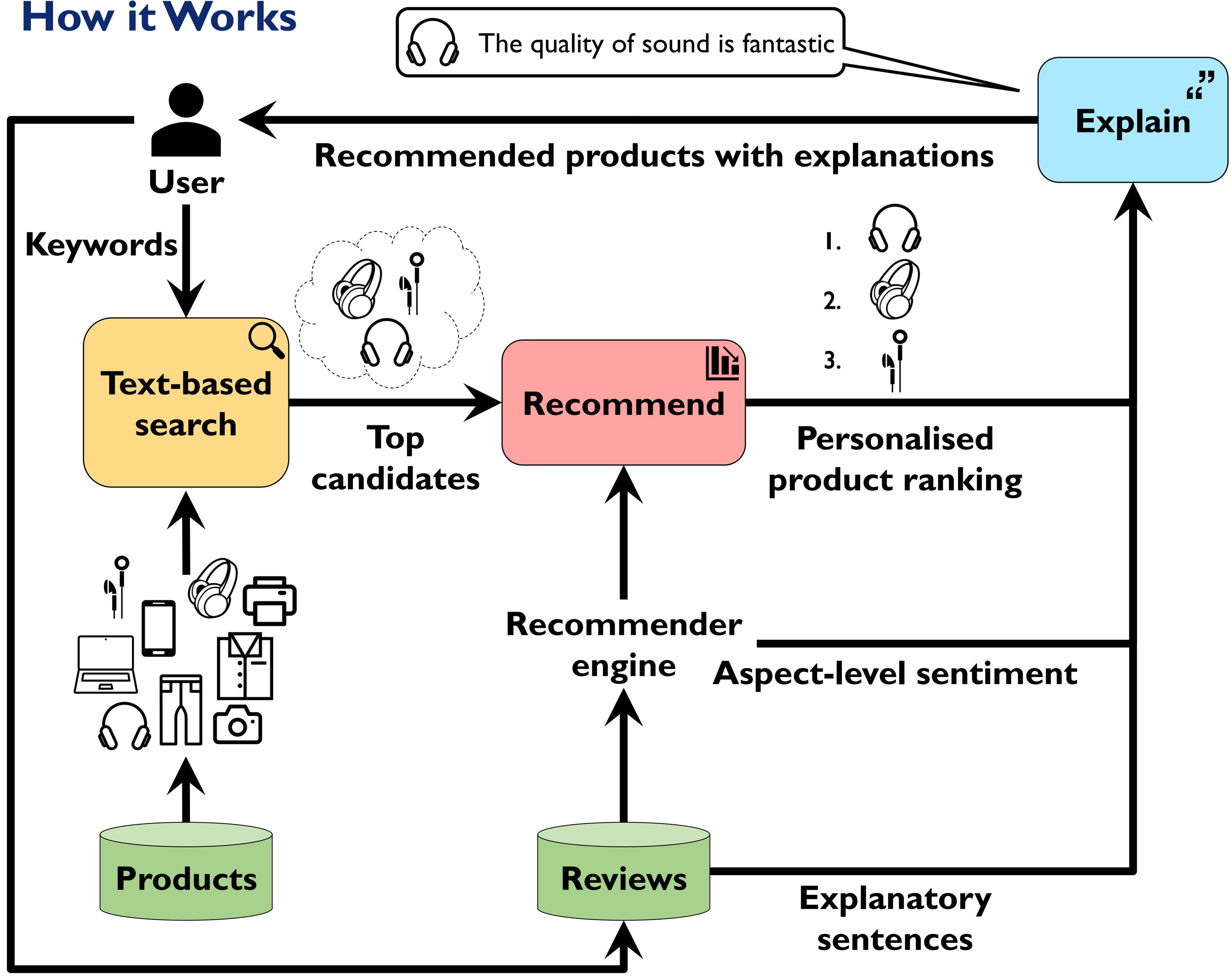
Explore by chatting with a user-friendly smart-system

- Clutter free – focus only on relevant products
- Convenient – view and edit past reviews at any time
- Customized – analyse user preferences over time

Meaningful explanations for smarter and swifter decisions

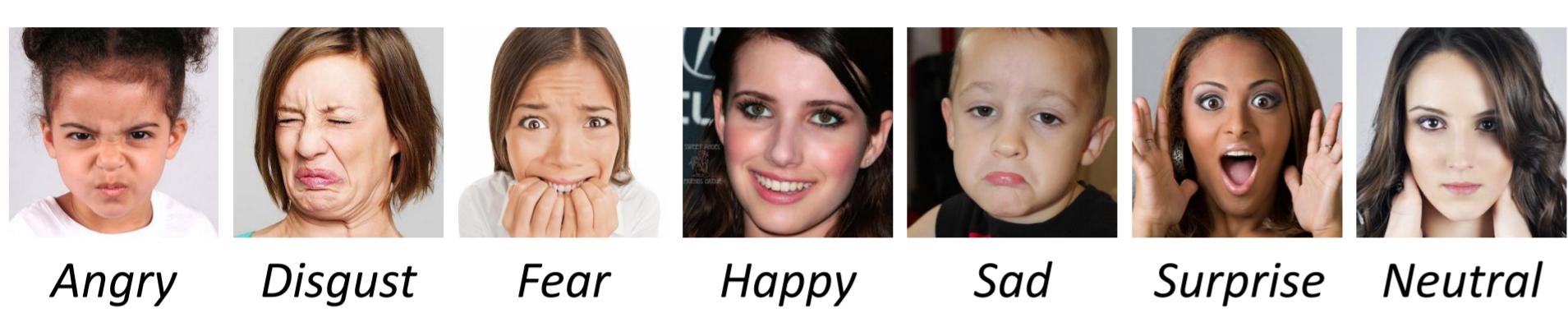
- Efficient – understand your recommendations at a glance
- Effective – compare only the features that matter most to you
- Evaluable – verify that our recommendations are tailored to your needs

How it Works

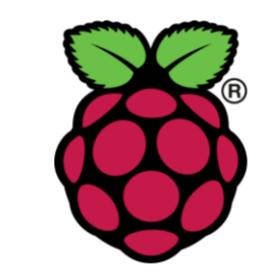


Lite Emotion Detection

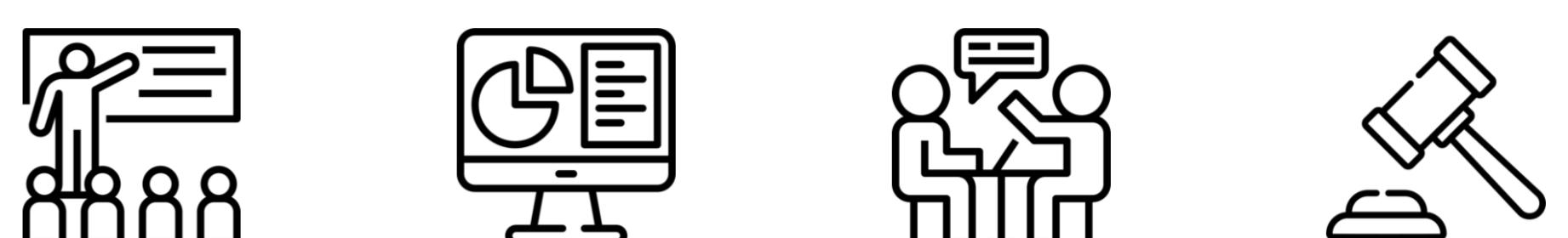
- FaceInMotion is built to detect human emotions from facial expressions
- The compact system is deployable on multiple platforms (e.g., mobile, IoT) with low latency yet high accuracy



Supported Platform

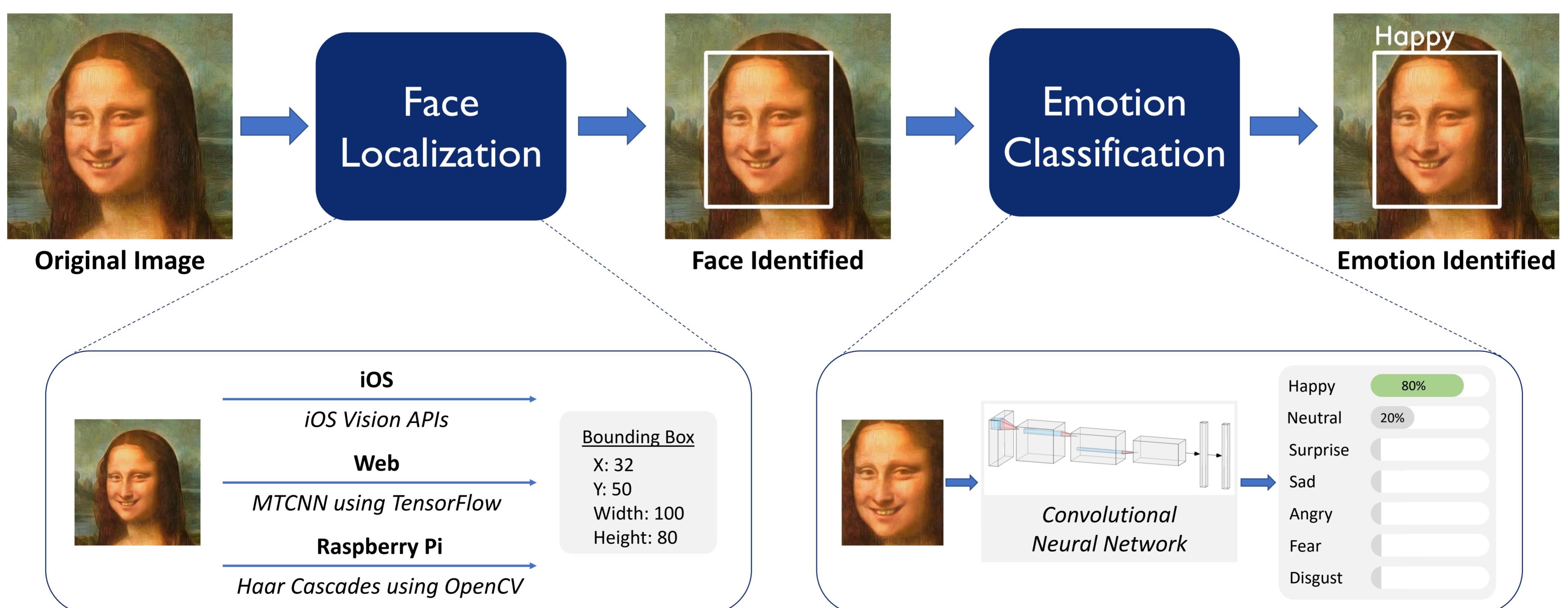


Potential Applications



- Education
Monitoring students' learning (e.g., identifying learning difficulties)
- Market Research
Analysing customers' sentiment (e.g., customers' response to products)
- Interviews
Profiling interviewees (e.g., confidence level)
- Law Enforcement
Detecting malicious intent (e.g., hostility)

Emotion Detection Process



Performance

- FER2013 dataset (Goodfellow et al. 2013)

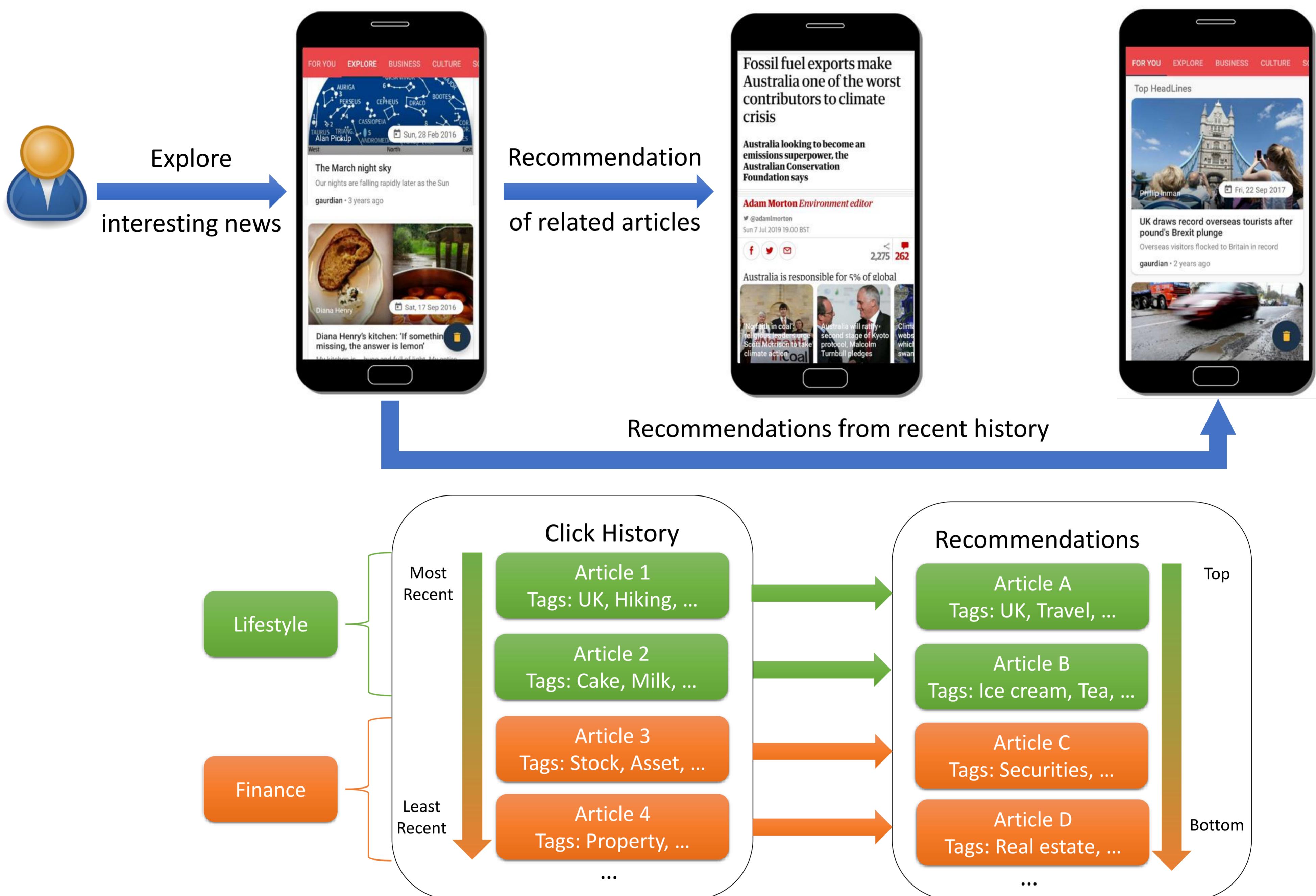
	Our Model (Ensembled)	Kaggle 1 st rank	Our Model (Single Model)	Kaggle 2 nd rank
Public Leaderboard	70.94%	69.77%	69.66%	69.07%
Private Leaderboard	73.25%	71.16%	70.24%	69.27%

- Deployed Model

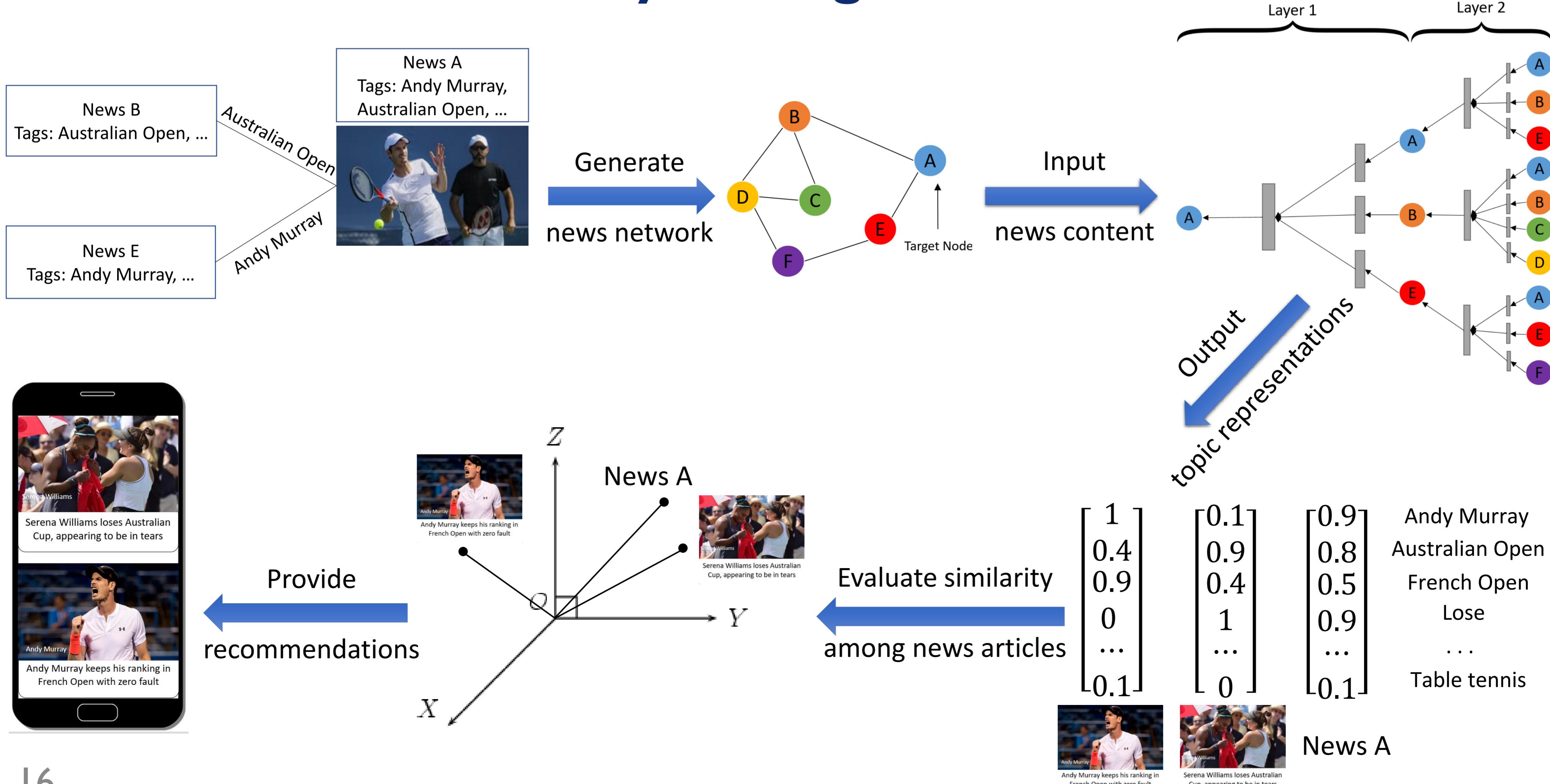
	Original	Optimized
Model Size	18.4MB	4.6MB (4x smaller)
Accuracy	70.24%	70.02% (-0.22%)
Speed	iOS Rasp. Pi	186 FPS 14 FPS
		231 FPS (1.24x faster)
		19 FPS (1.35x faster)

MindReader is a news recommendation app that provides **personalized recommendations** based on an individual's **reading history**.

Generating Recommendations



How to Assess Similarity Among News Articles



- Provides a browser-friendly, time-saving code generator for neural network (NN) models, customizable to suit your needs
- Facilitates NN education and builds a better understanding of the models
- Generates ready-to-use-and-deploy systems for businesses

Machine Learning in Your Browser

Design neural network models via an intuitive visual language

PREFERRED.AI

Neural Network Lab

Layers

- Conv2D
- MaxPooling
- Flatten
- Dense
- Dropout
- Reshape
- GAPID
- LSTM
- Embedding
- Output
- Text Annotation

Cut Copy Paste Undo Redo Save Load Compile

Data is processed by layers of neurons

Input

Output

Properties

Compile code to initialise model

filters: 1
strides: 1x 1x
activation: relu
useBias: true

Drag-and-drop layers with customisable parameters

In-browser training

```
5 var x1 = tf.layers.conv2d({
11 }).apply(input);
12
13 var x2 = tf.layers.maxPooling2d({
14   trainable: true,
15   updateable: false
16 }).apply(x1);
17
18 var x3 = tf.layers.dropout({
19   rate: 0.1
20 }).apply(x2);
21
22 var x4 = tf.layers.flatten({
23   trainable: true,
24   updateable: false
25 }).apply(x3);
26
```

Download the code and the trained model

The NN model 'learns' to perform certain tasks by passing examples through it for training

Evaluation

Layer Name	Output Shape	# Of Params	Trainable
input1	[batch,28,28,1]	0	false
conv2d_Conv2D1	[batch,26,26,1]	10	true
max_pooling2d_MaxPooling2D1	[batch,13,13,1]	0	true
dropout_Dropout1	[batch,13,13,1]	0	true
flatten_Flatten1	[batch,169]	0	true
dense_Dense1	[batch,10]	1,700	true

onBatchEnd

A code editor for further customisation

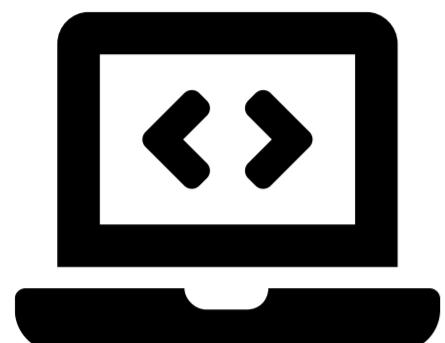
Model summary, training statistics and predictions

Links

Contact us to:



get involved in our projects as interns or research assistants

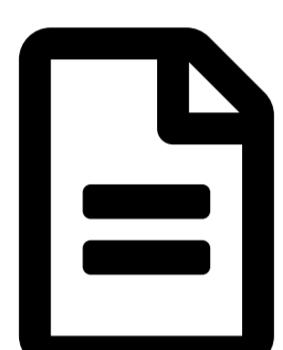


use our libraries or license our technologies



or just join us already

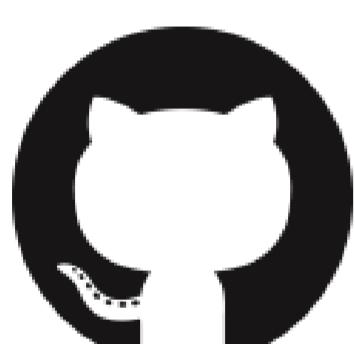
We are also on:



<https://preferred.ai/publications/>



<https://preferred.ai/>



<https://code.preferred.ai>



<https://preferred.ai/videos>



<https://preferred.ai/join/>

Learn more about SMU's Postgraduate Programmes:

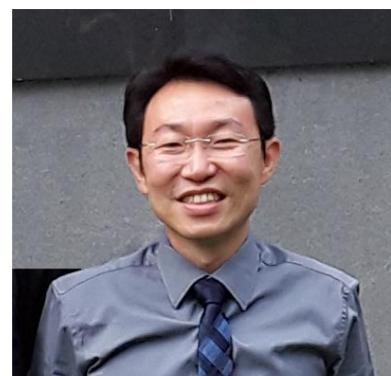
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Programmes

<https://graduatestudies.smu.edu.sg>

School of
Information Systems

<https://sis.smu.edu.sg/programmes/postgraduate>

TECHFEST.PREFERRED.AI 2019 Organizing Team



Hady Lauw



Aghiles Salah



Maksim Tkachenko



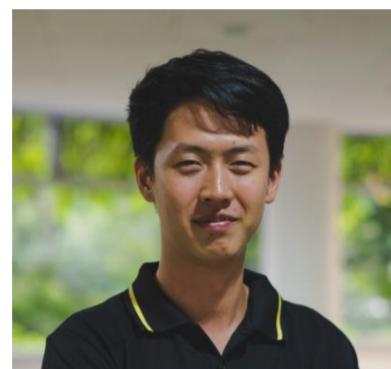
Andrew Le Duy Dung



Trong Quoc Tuan



Le Trung Hoang



Chia Chong Cher



Zhang Ce



Lee Ween Jiann



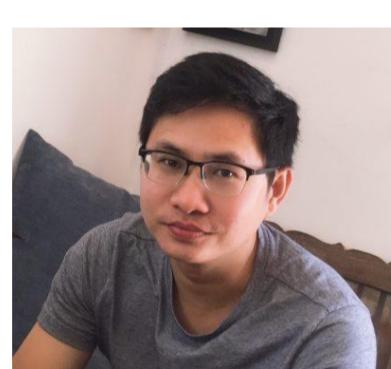
Darryl Ong



Guo Jingyao



Huynh Phu Minh



Tran Thanh Binh



Abhyuday Sammadder



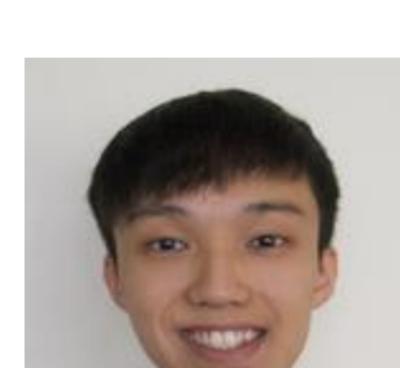
Aw Jiayu



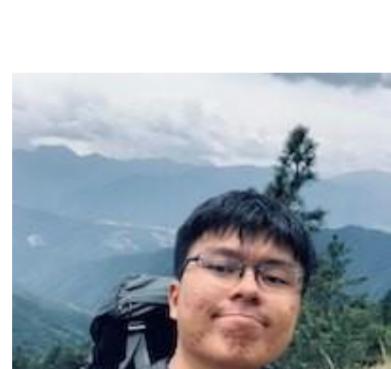
Cao Wanyue



Cheryl Lim Wei Lin



Choy Kar Sen



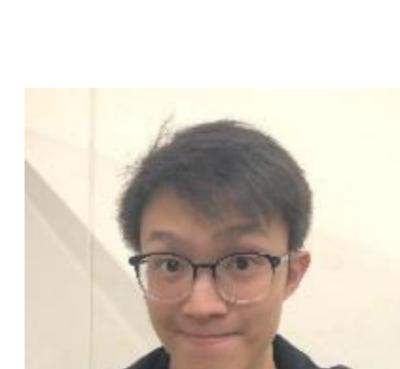
Hee Ming Shan



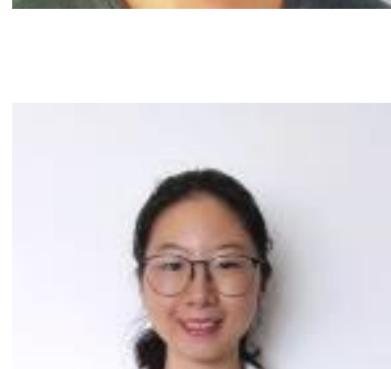
Liu Ziyuan



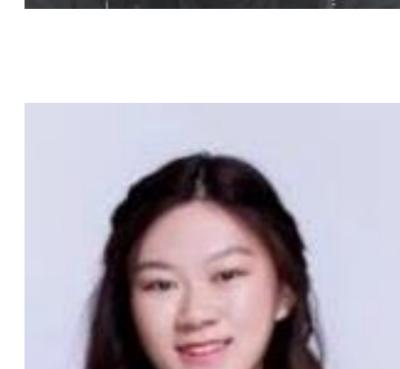
Lyu Cheng



Ngoh Yi Long



Steffi Tan Xin Rong



Wei Ming

We would also like to acknowledge the other contributors to the various projects exhibited in this TechFest, who though unnamed are much appreciated.

PREFERRED.AI

We would love to hear your comments:

<https://techfest.preferred.ai/feedback>