LINKE

Lab for Intelligent Networking
and Knowledge Engineering

High-Quality Activity-Level Video Advertising

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University of Science and Technology of China

Tencent 腾讯

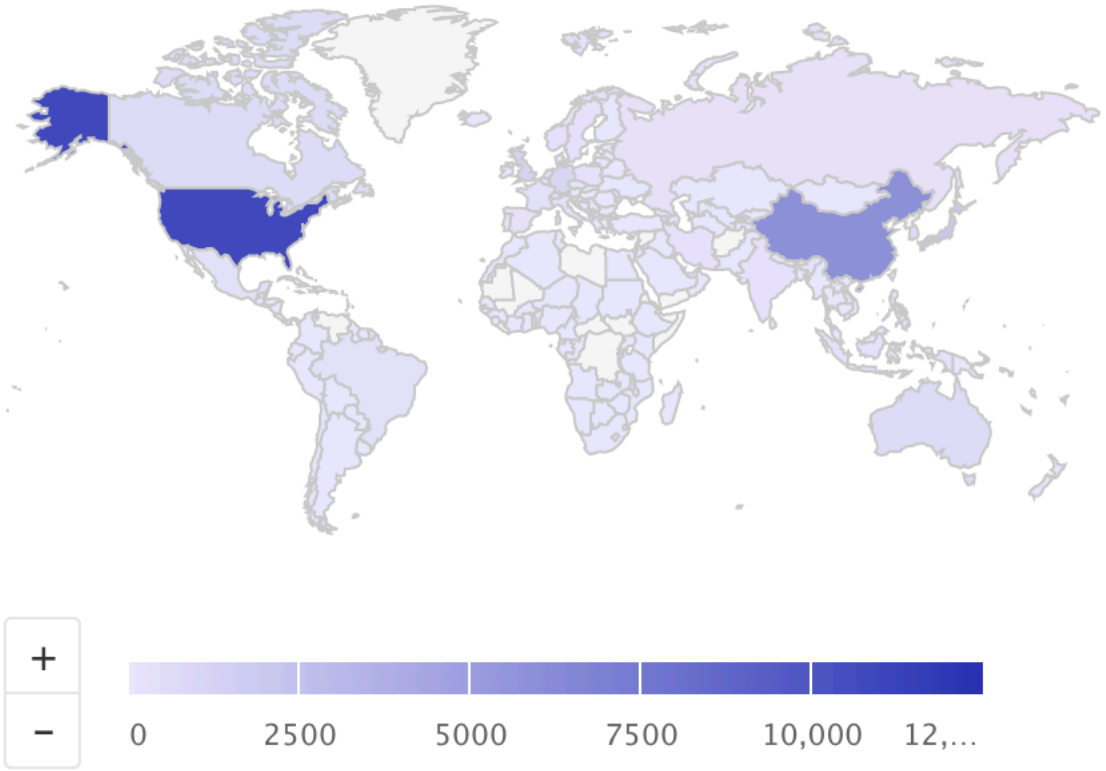
Outline

- **Introduction**
- Multimodal Content Embedding
- Activity-Level Video Advertising
- Evaluation
- Conclusion

Introduction

Billion-Dollar Business

2020 Video Advertising Market Volume

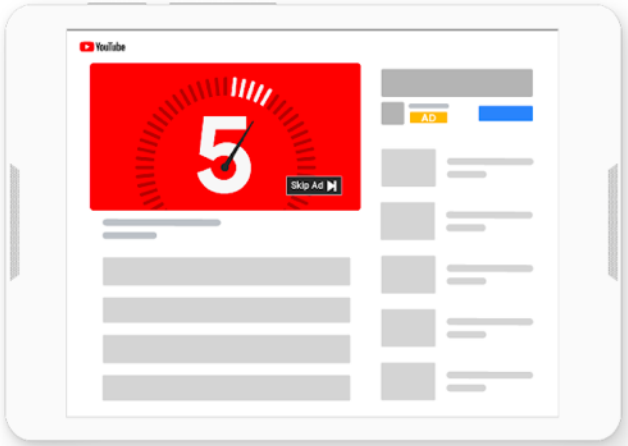


Top 5	
1. United States	**US$10,857m**
2. China	US$5,897m
3. Japan	US$2,153m
4. United Kingdom	US$1,222m
5. Germany	US$1,035m

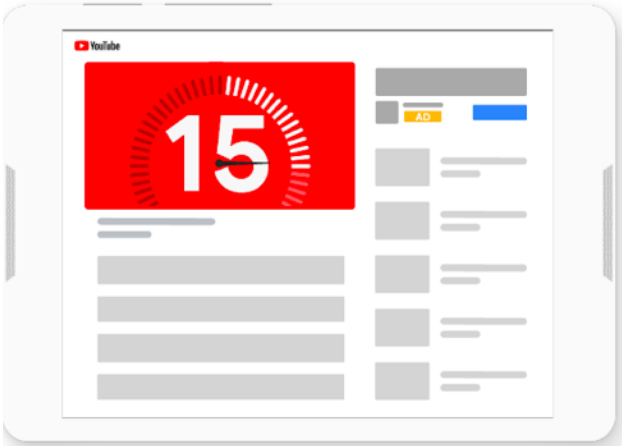
https://www.statista.com/outlook/218/109/video-advertising/united-states#market-globalRevenue

Introduction

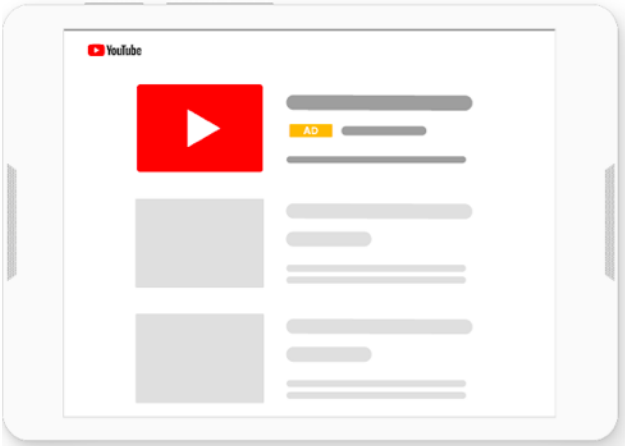
Video Advertising Formats



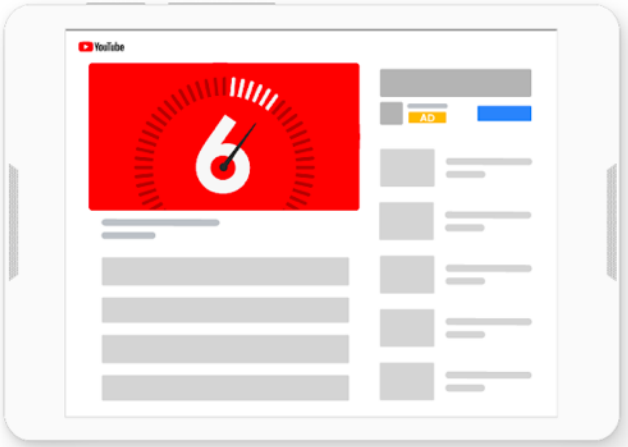
Skippable In-Stream Ads



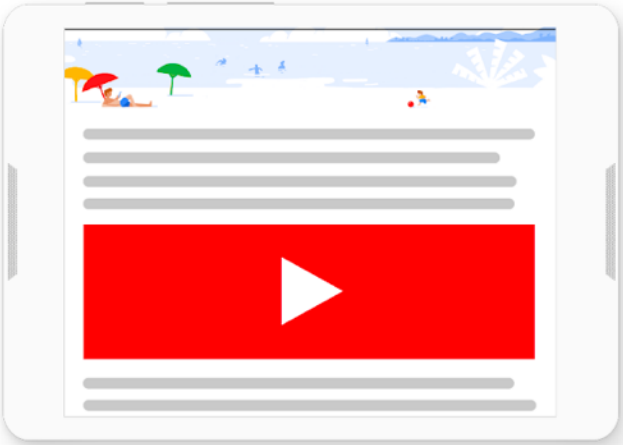
Non-Skippable In-Stream Ads



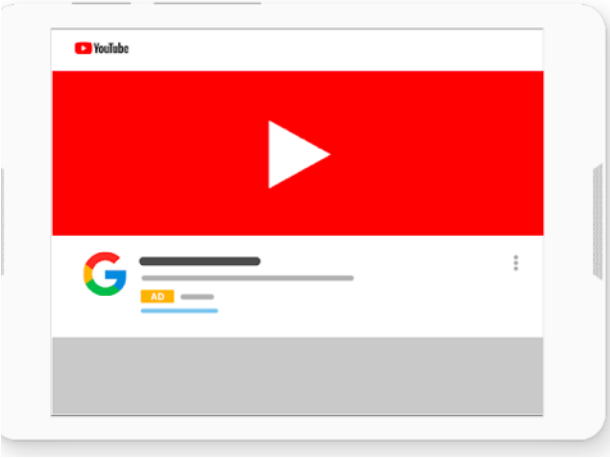
Video Discovery Ads



Bumper Ads



Out-Stream Ads

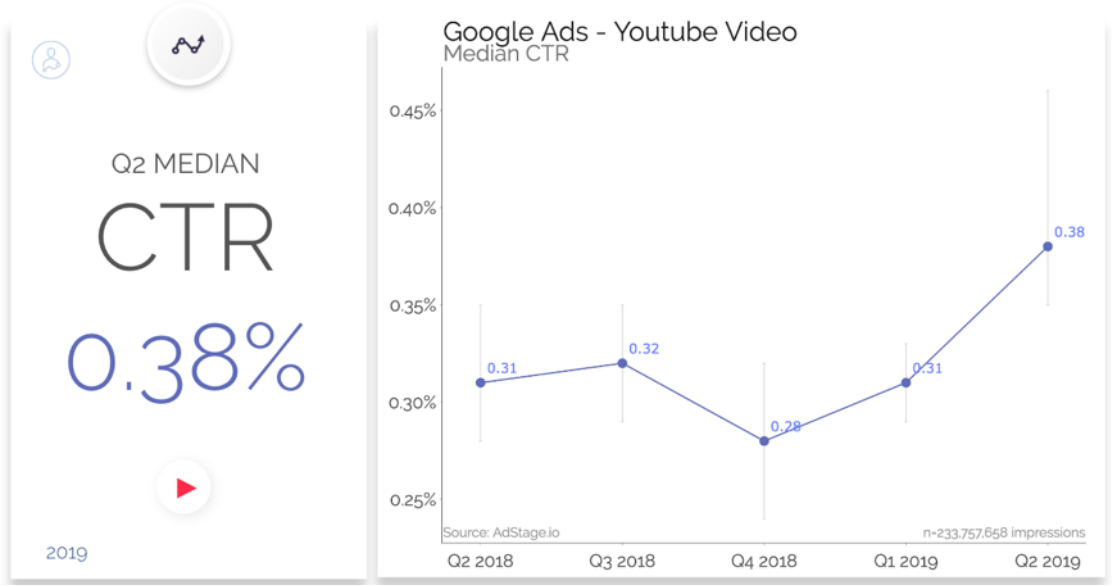


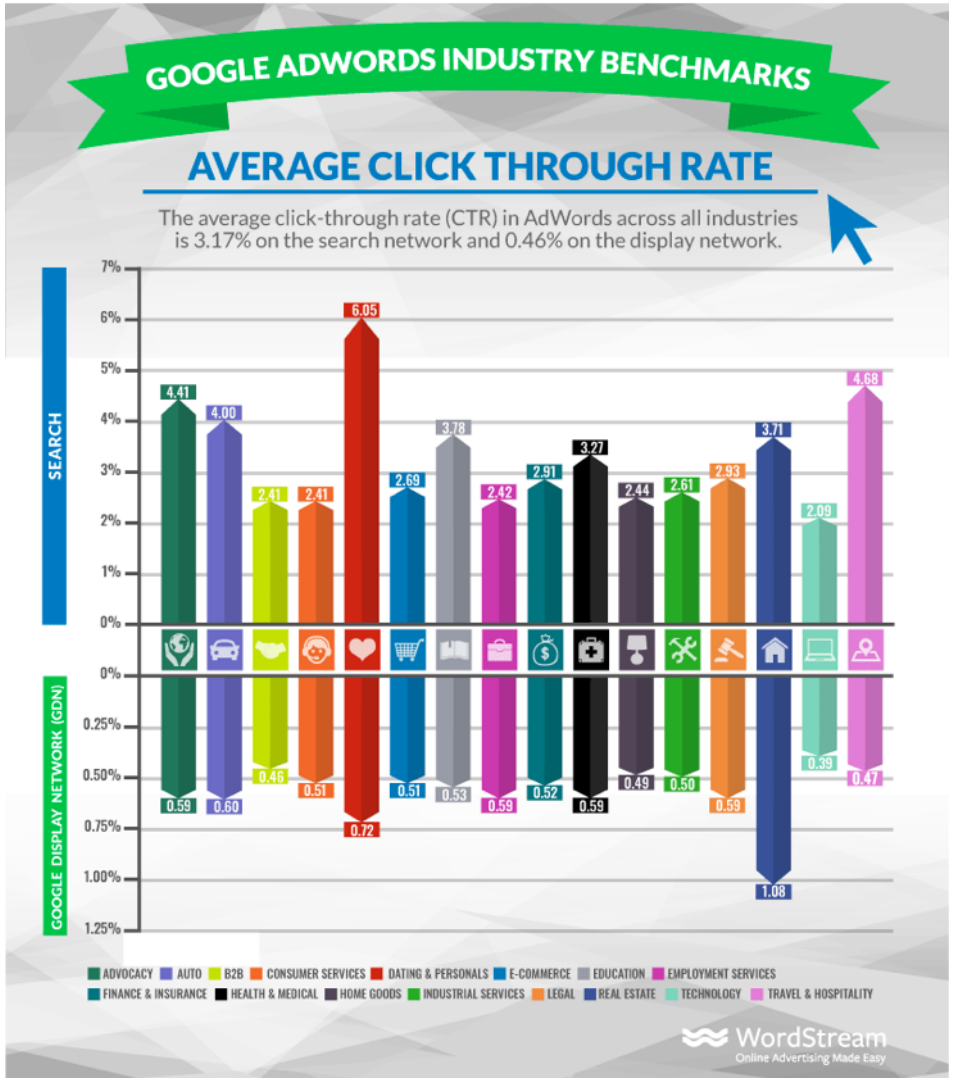
Masthead Ads

https://support.google.com/google-ads/answer/2375464?hl=en

Introduction

Low CTR Compared with Traditional Ads





Youtube 0.38% << AdWords 3.17%

https://blog.adstage.io/youtube-benchmarks-cpc-cpm-and-ctr
https://www.wordstream.com/blog/ws/2016/02/29/google-adwords-industry-benchmarks

Introduction

Content-Related Video Advertising

Will you marry me?

Diamond Rings
White Sapphire 58...
HK$3,928.00
Glamira HK

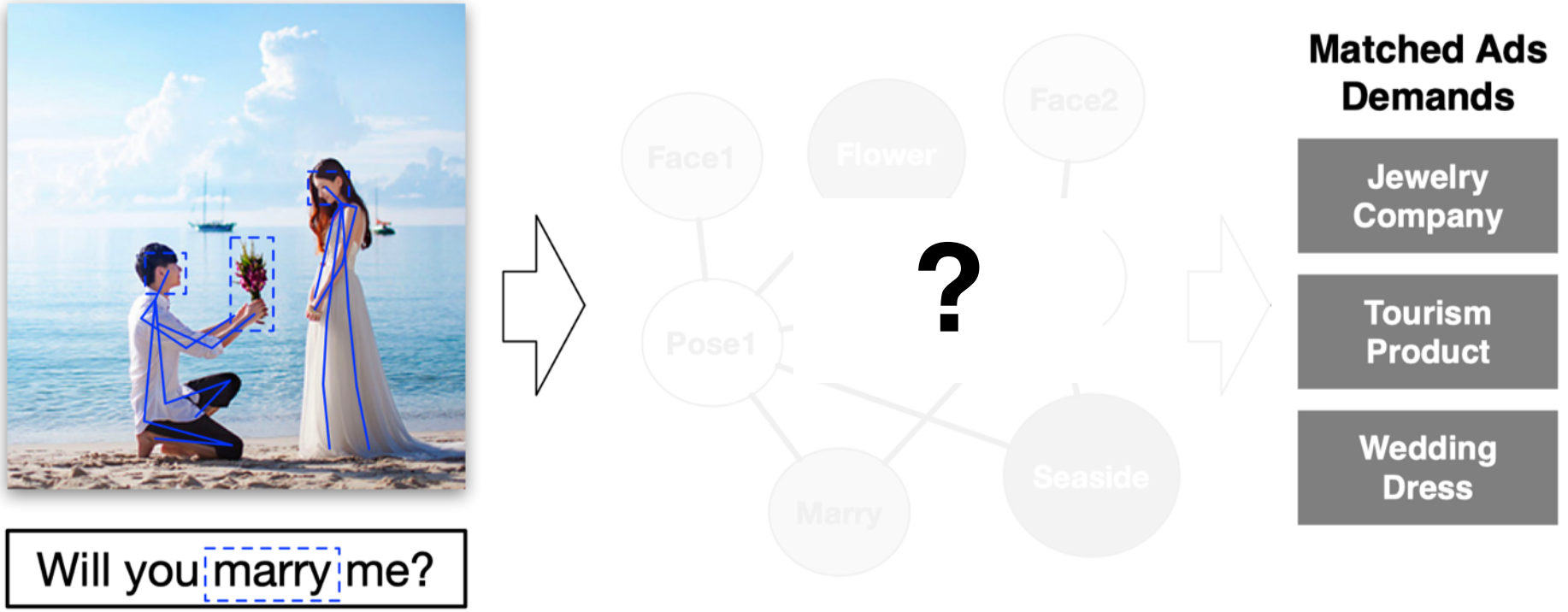
LoveShackFancy
Irene Gown in Whi...
HK$9,262.70
revolve.com

Matched Ads Demands

- Jewelry Company
- Tourism Product
- Wedding Dress

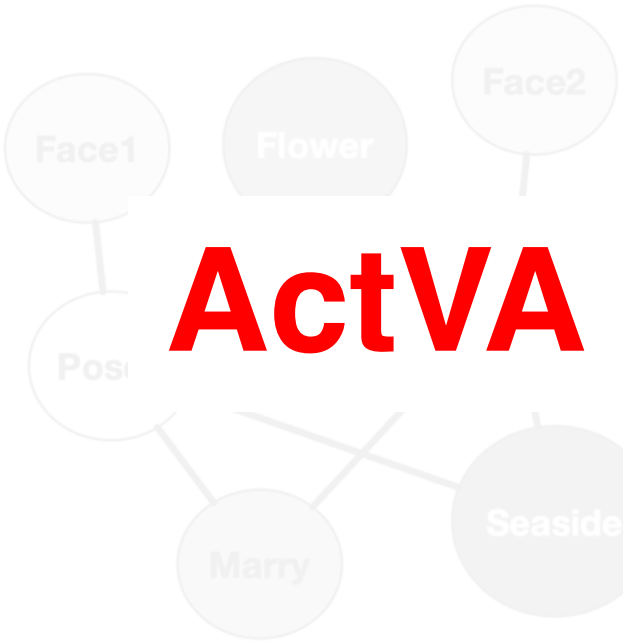
Introduction

Content-Related Video Advertising



Introduction

Activity-Level Video Advertising



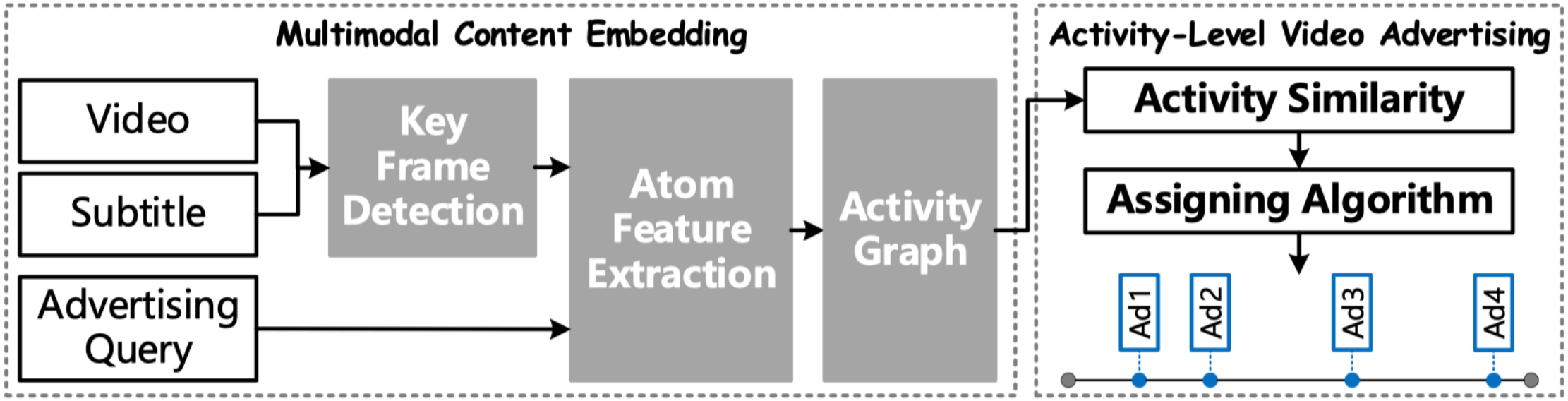
Matched Ads Demands

- Jewelry Company
- Tourism Product
- Wedding Dress

Introduction

Activity-Level Video Advertising

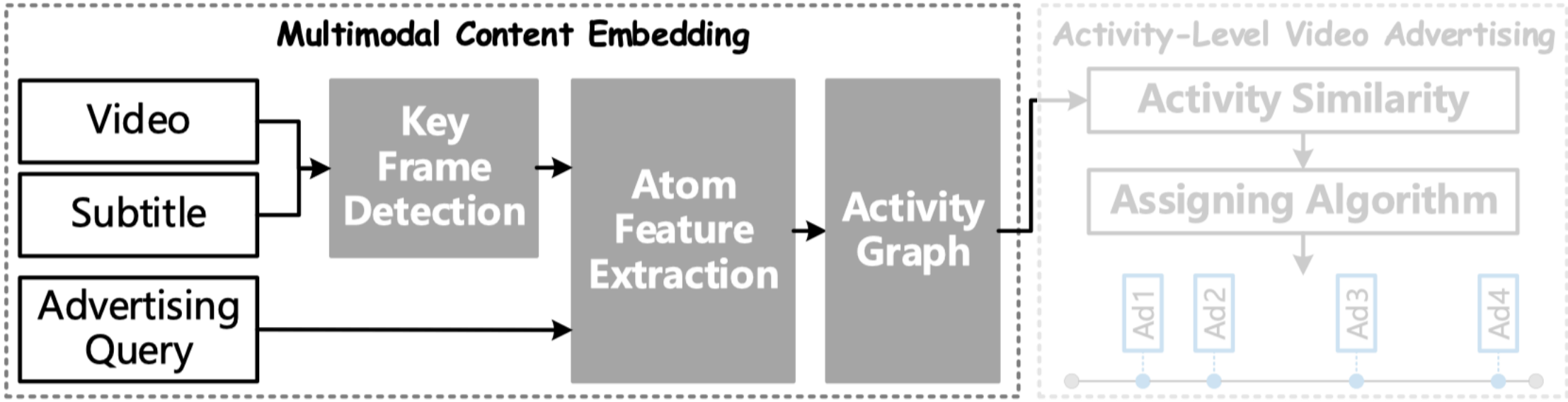
Main Contributions



1. The first non-predefined activity-level video advertising system;
2. Effective algorithm for optimizing advertising service over content relevance, revenue and intrusiveness perception.

Activity-Level Video Advertising

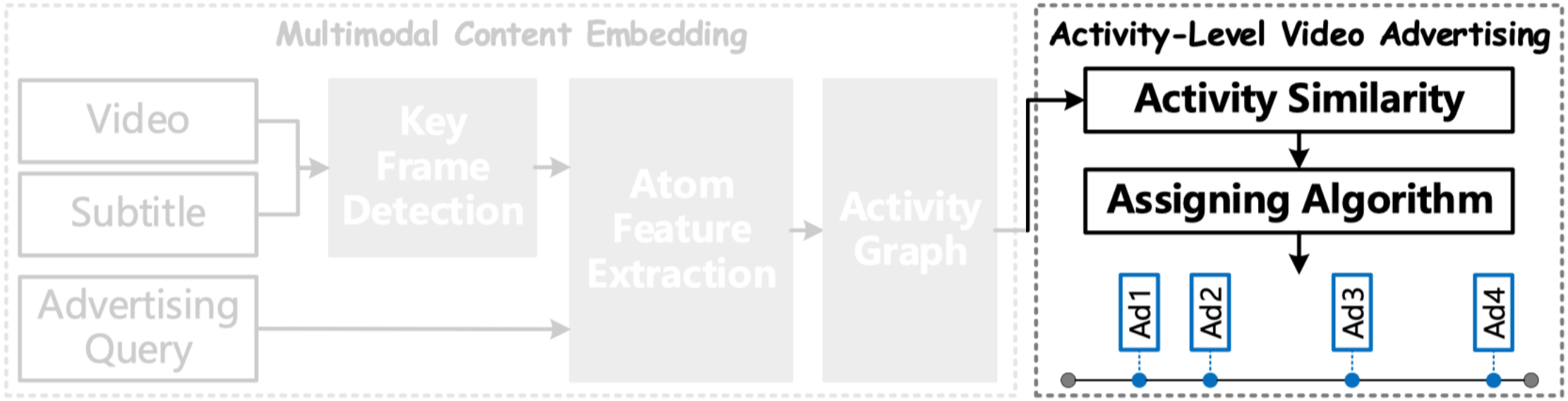
System Framework



Step#1: Find possible ads positions.

Activity-Level Video Advertising

System Framework



Step#2: Assign ads properly.

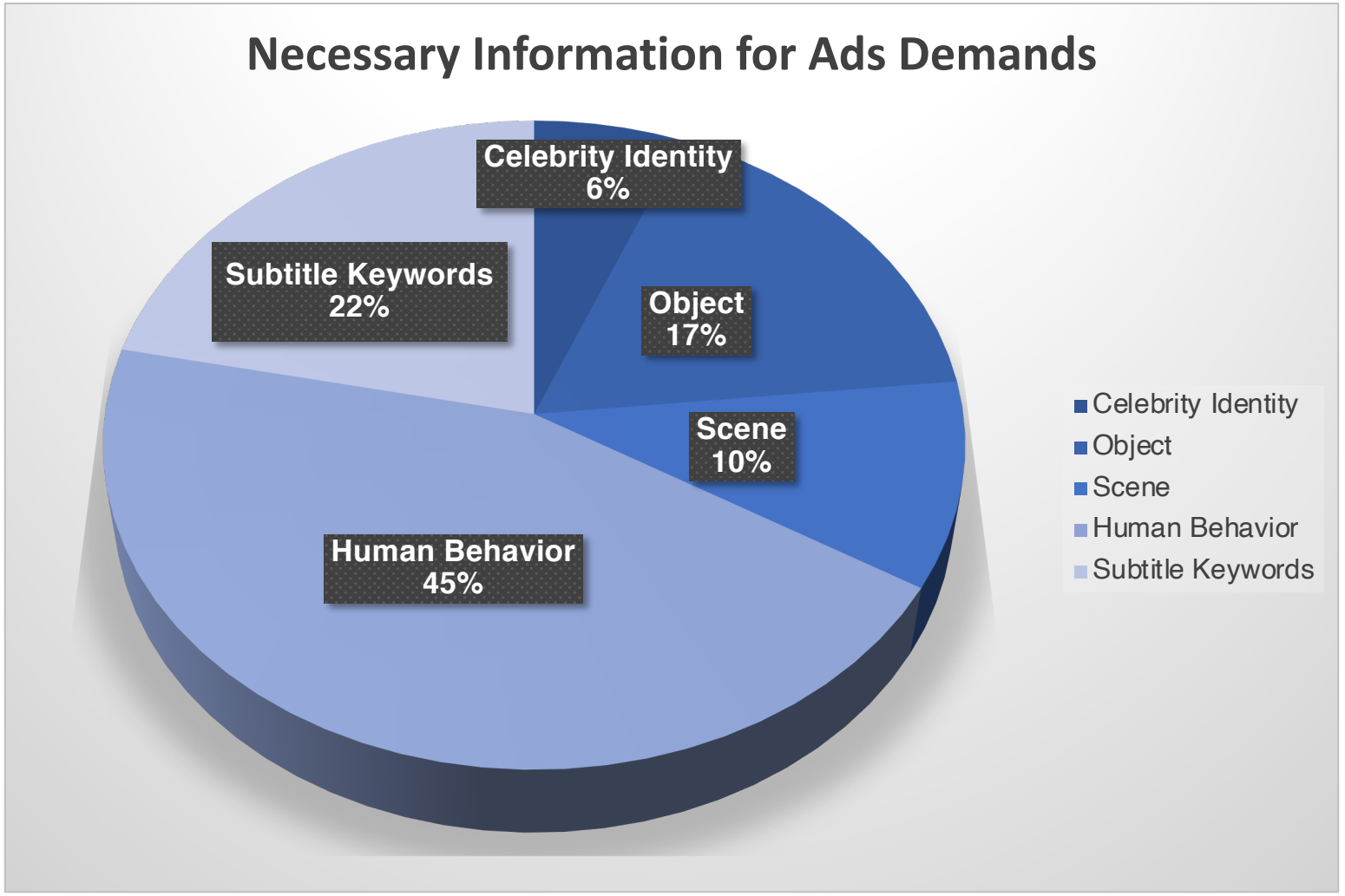
Outline

- Introduction
- **Multimodal Content Embedding**
- Activity-Level Video Advertising
- Evaluation
- Conclusion

Multimodal Content Embedding

Market Research @ Tencent

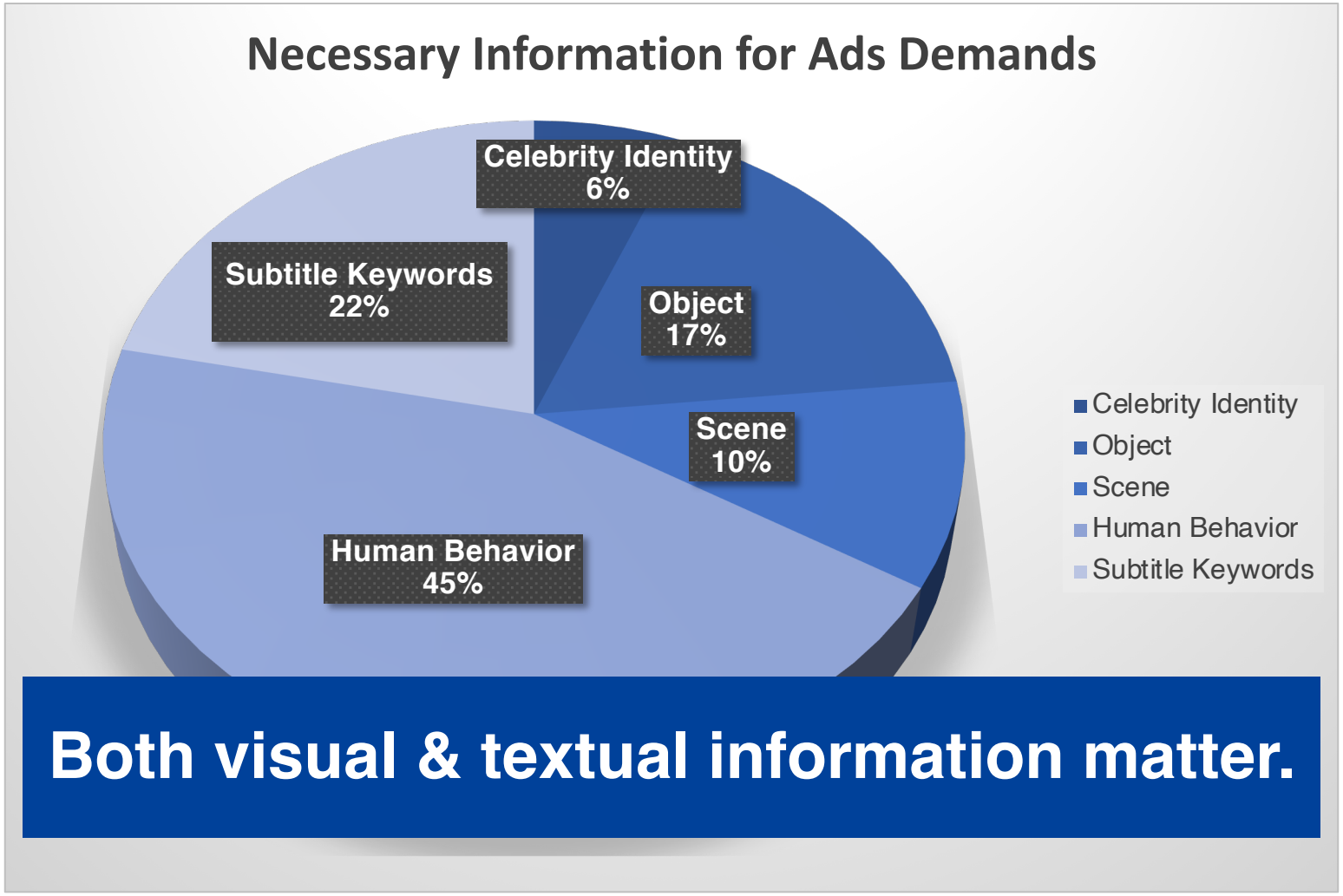
150 Content-Targeted Advertising Needs



Multimodal Content Embedding

Market Research @ Tencent

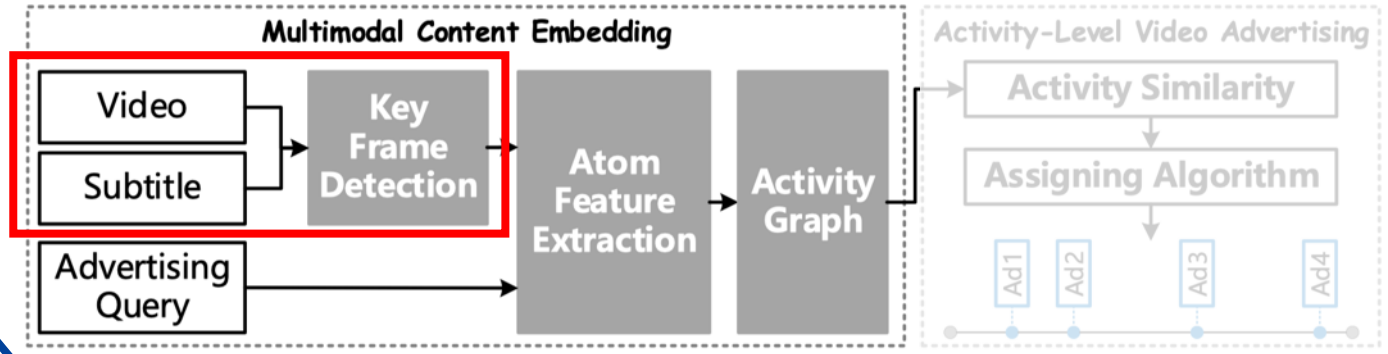
150 Content-Targeted Advertising Demands



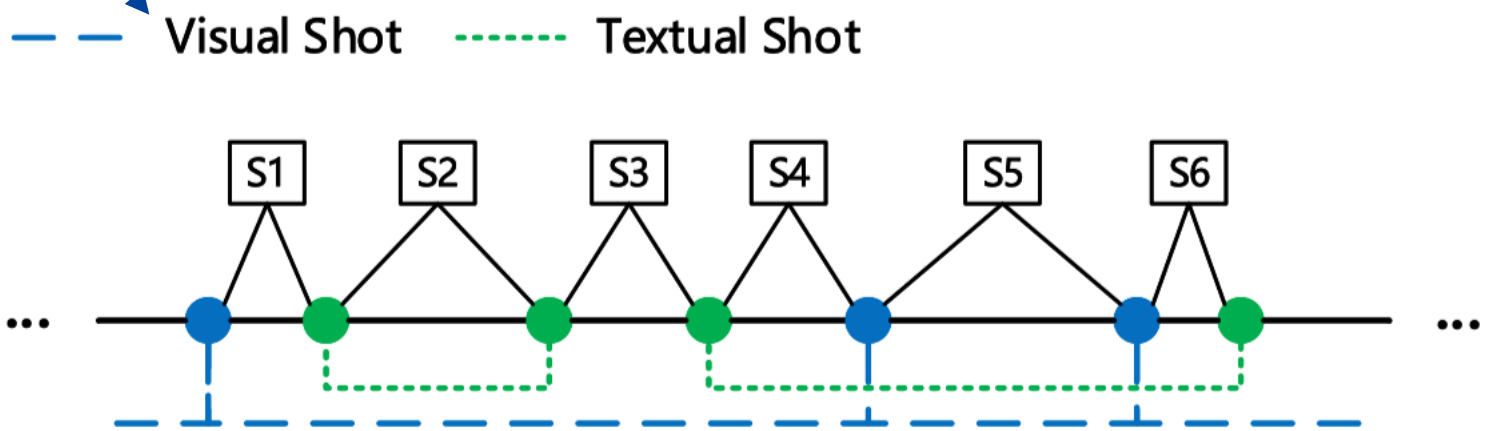
Both visual & textual information matter.

Multimodal Content Embedding

Key Frame Detection

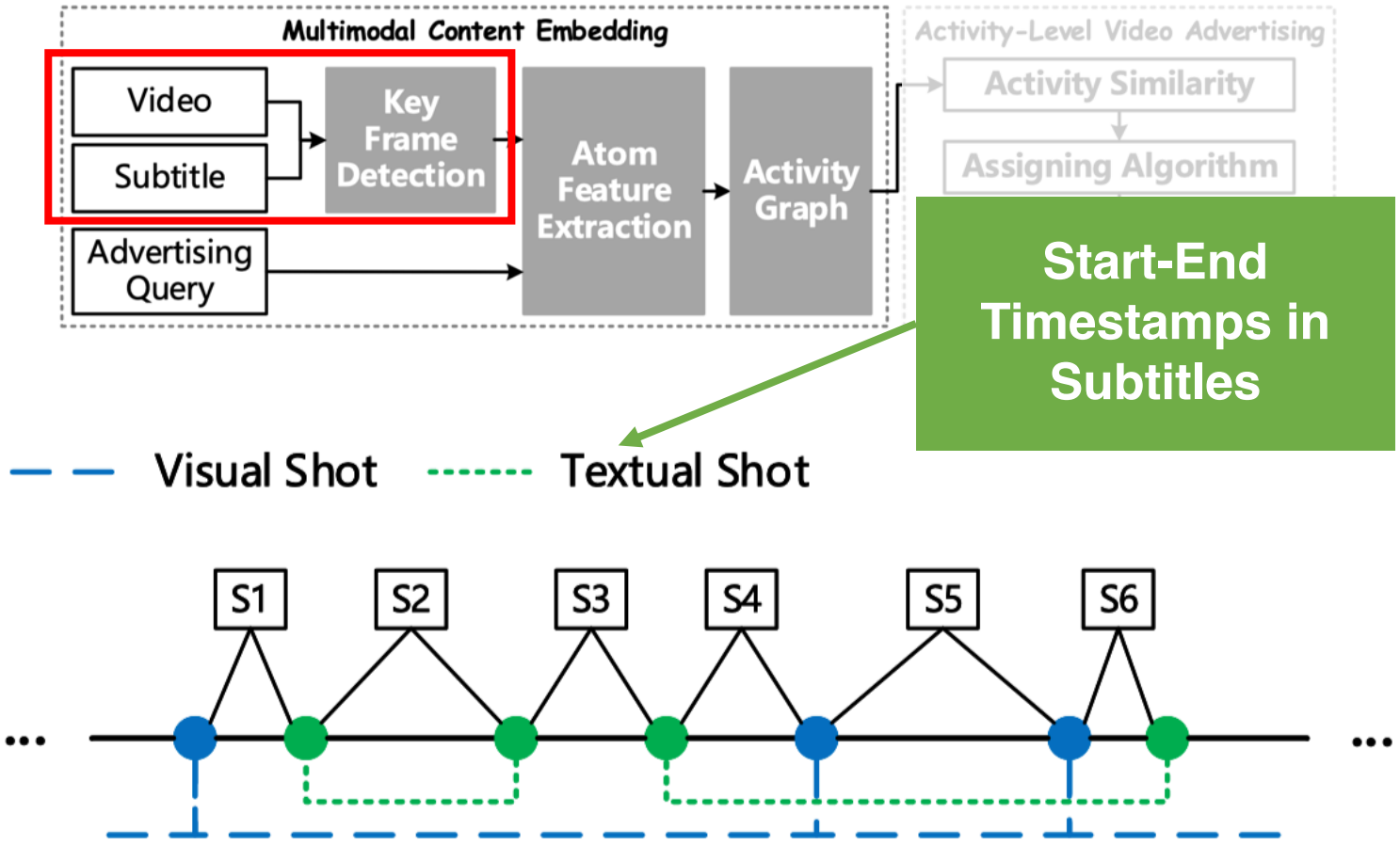


Color-Histogram based Shot Detection



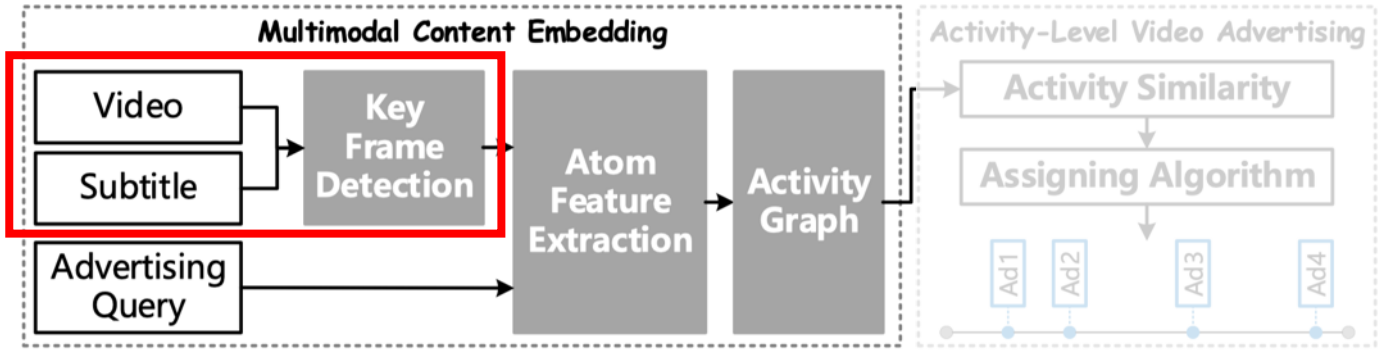
Multimodal Content Embedding

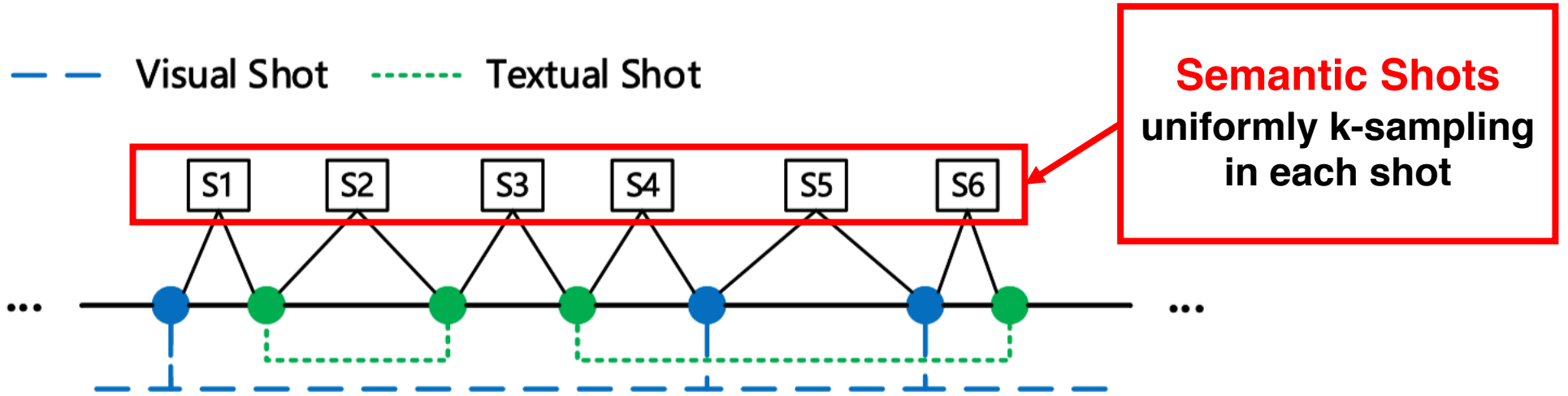
Key Frame Detection



Multimodal Content Embedding

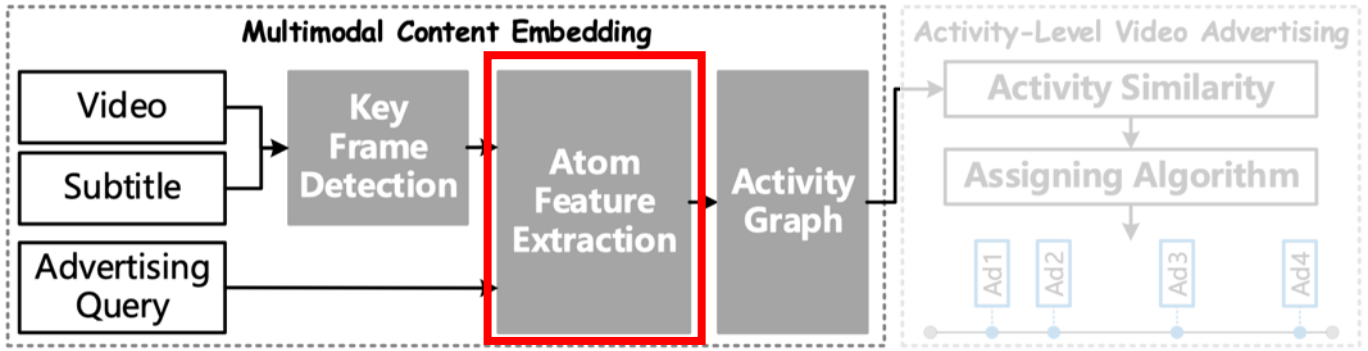
Key Frame Detection

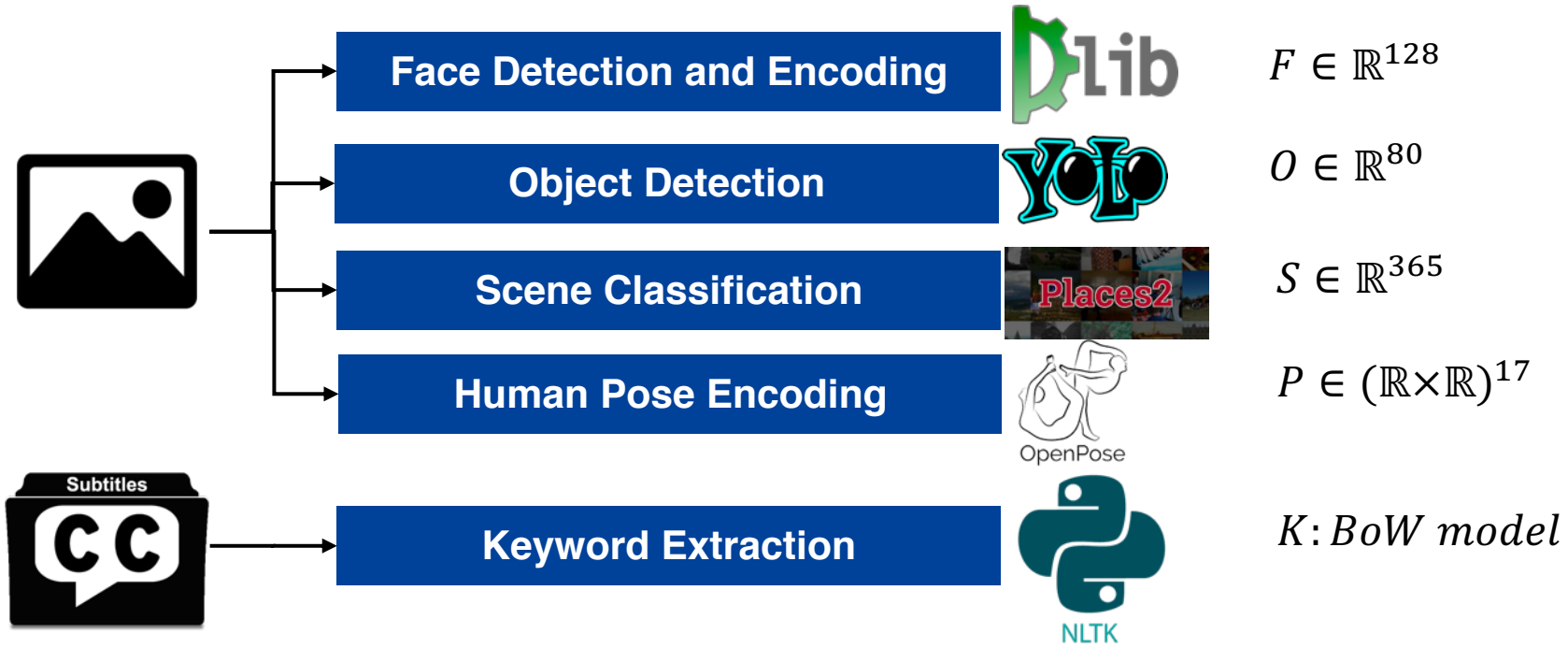




Multimodal Content Embedding

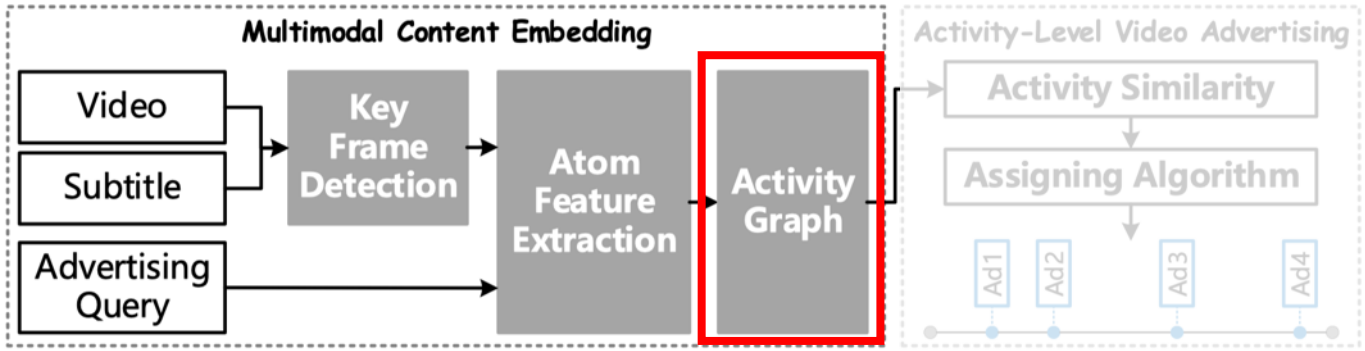
Atom Feature Extraction



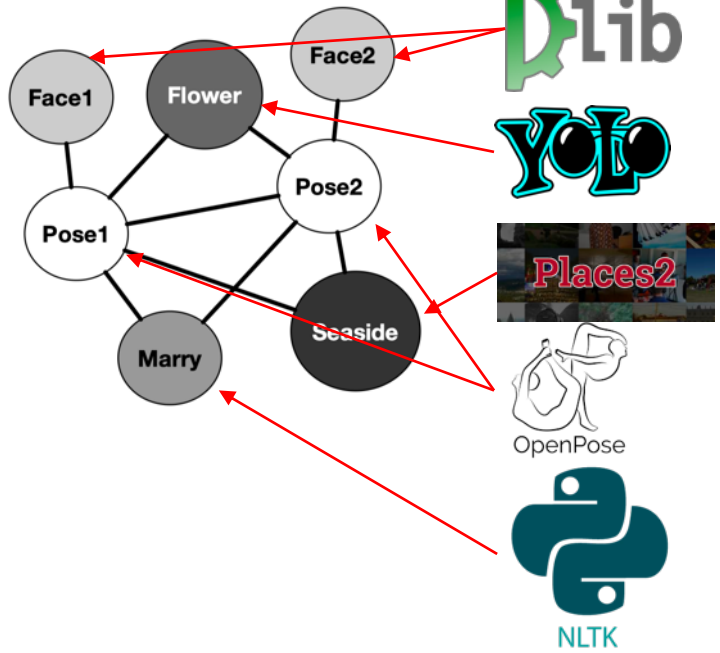


Multimodal Content Embedding

Activity Graph Representation



Vertices



$F \in \mathbb{R}^{128}$

$O \in \mathbb{R}^{80}$

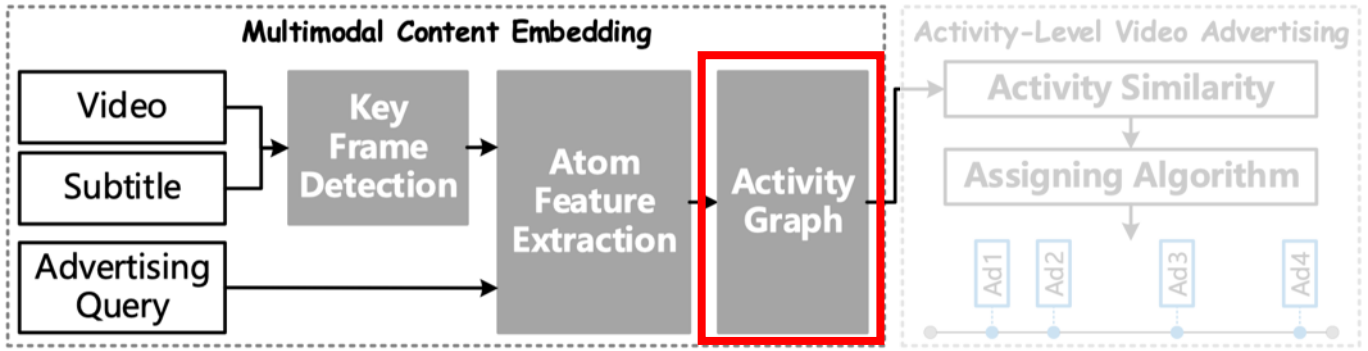
$S \in \mathbb{R}^{365}$

$P \in (\mathbb{R}\times\mathbb{R})^{17}$

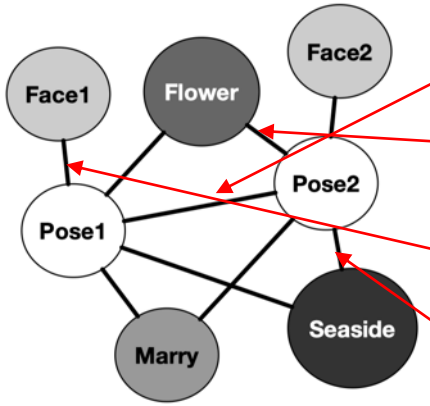
$K: BoW\ model$

Multimodal Content Embedding

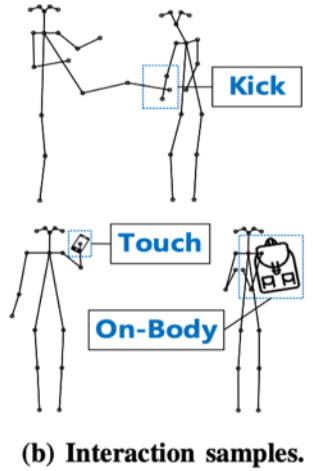
Activity Graph Representation



Edges



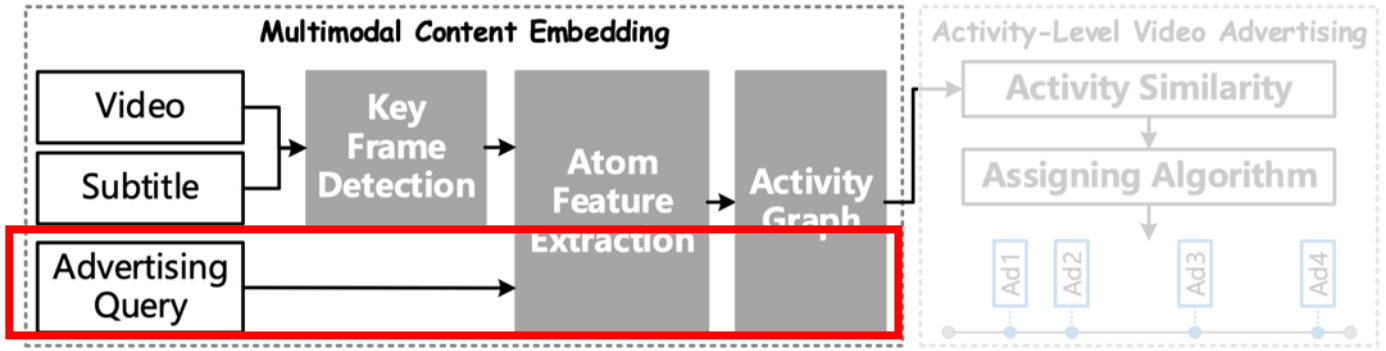
- **Pose-Pose Interaction** $R_{pp}: P \times P \rightarrow \mathbb{N}$
- **Pose-Object Interaction** $R_{po}: P \times O \rightarrow \mathbb{N}$
- **Pose-Face Matching** $R_{pf}: P \times F \rightarrow \mathbb{N}$
- **Pose-Scene Correlation** $R_{ps}: P \times S \rightarrow \mathbb{R}$

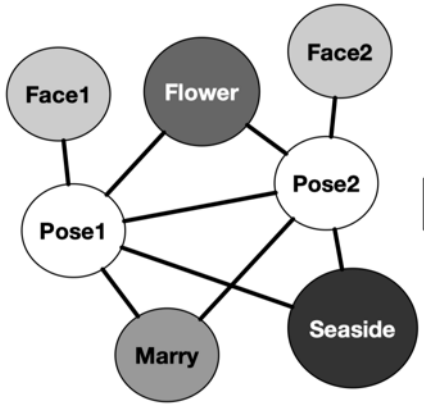


(b) Interaction samples.

Multimodal Content Embedding

Activity Graph Representation





marry, travel, jewelry, ...

Outline

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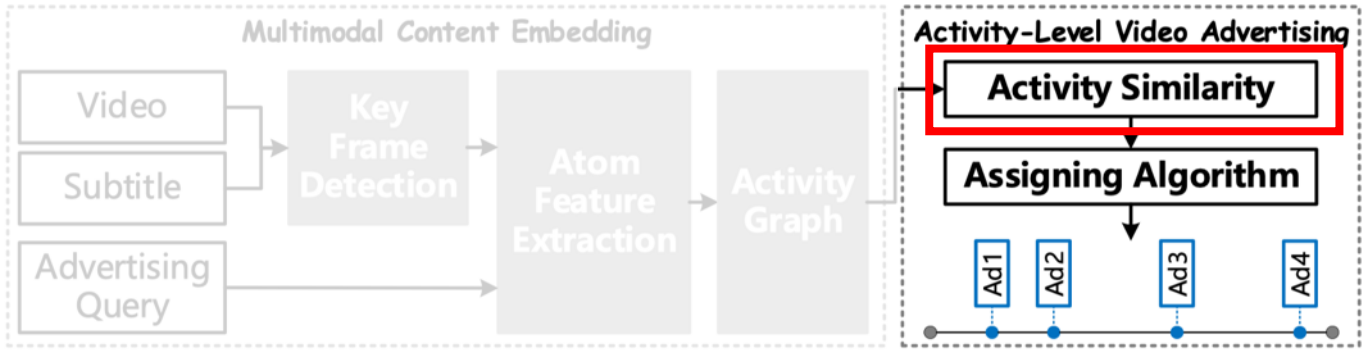
- Conclusion

Activity-Level Video Advertising

Activity Similarity



Face / Human Pose

$x = (encoding, confidence)$

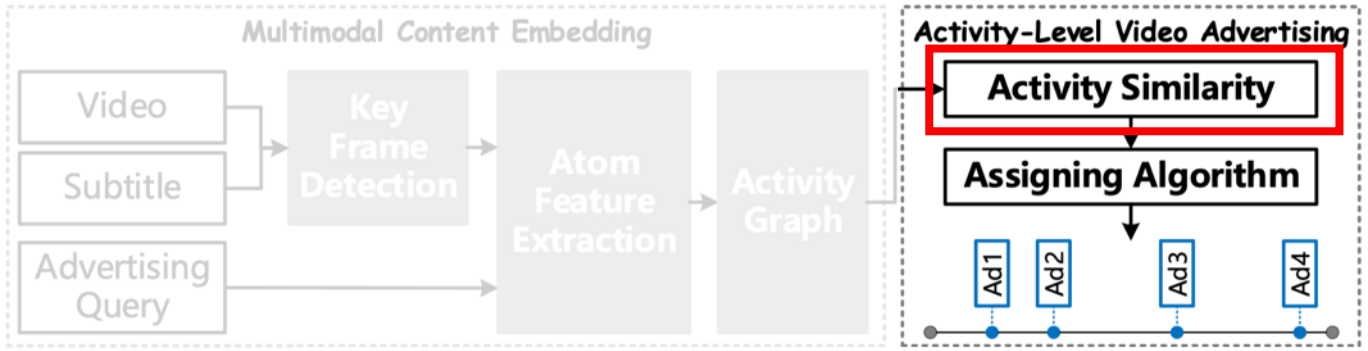
Atom-Feature / Vertex Similarity

$$s_1(x_1, x_2) = 1 - \frac{1}{|enc_1|} \sum_{\substack{e_i \in enc_1 \\ c_i \in conf_1}} \min_{\substack{e_j \in enc_2 \\ c_j \in conf_2}} \frac{\theta_1 ||e_i - e_j||_2}{(1 + \min(c_i, c_j))}$$

Interaction / Edge Similarity

Activity-Level Video Advertising

Activity Similarity



Atom-Feature / Vertex Similarity

Face / Human Pose

$x = (encoding, confidence)$

Object / Scene / Keyword

$x = (category, confidence)$

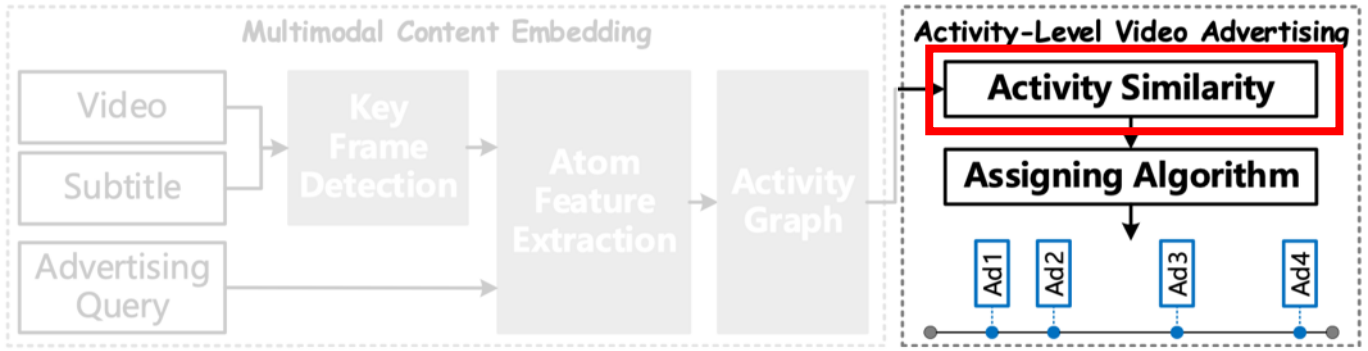
$$s_1(x_1, x_2) = 1 - \frac{1}{|enc_1|} \sum_{\substack{e_i \in enc_1 \\ c_i \in conf_1}} \min_{\substack{e_j \in enc_2 \\ c_j \in conf_2}} \frac{\theta_1 ||e_i - e_j||_2}{(1 + \min(c_i, c_j))}$$

$$s_2(x_1, x_2) = \frac{1}{|cls_1|} \sum_{\substack{e_i \in cls_1 \\ c_i \in conf_1}} \max_{\substack{e_j \in cls_2 \\ c_j \in conf_2}} (\theta_2 \min(c_i, c_j) \rho(e_i, e_j))$$

Interaction / Edge Similarity

Activity-Level Video Advertising

Activity Similarity



Atom-Feature / Vertex Similarity

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$x = (encoding, confidence)$

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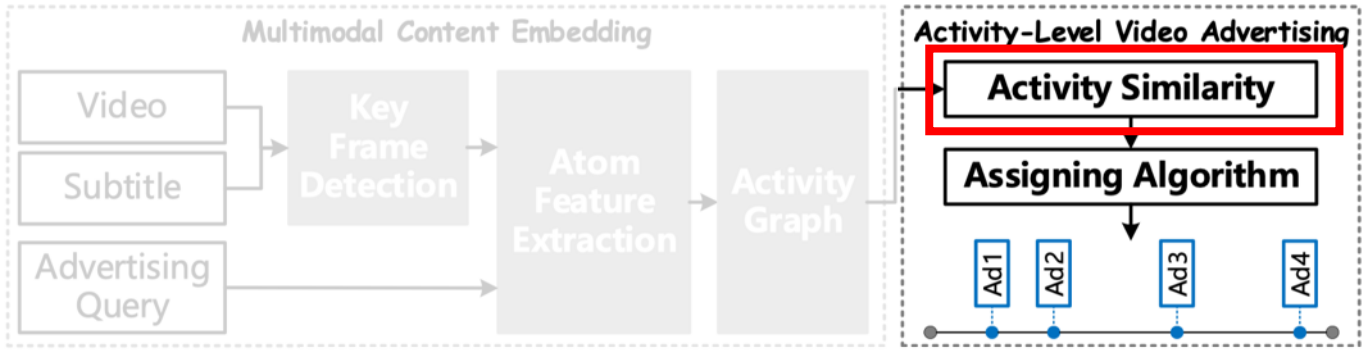
Interaction / Edge Similarity

Pose-Scene
numerical

$$s_3(e_i, e_j) = \begin{cases} 1 - ||e_i - e_j||_2, & \text{numerical} \\ \rho(e_i, e_j), & \text{categorical} \end{cases}$$

Activity-Level Video Advertising

Activity Similarity



Atom-Feature / Vertex Similarity

- **Face / Human Pose**
  $x = (encoding, confidence)$
- **Object / Scene / Keyword**
  $x = (category, confidence)$

$$s_1(x_1, x_2) = 1 - \frac{1}{|enc_1|} \sum_{\substack{e_i \in enc_1 \\ c_i \in conf_1}} \min_{\substack{e_j \in enc_2 \\ c_j \in conf_2}} \frac{\theta_1 ||e_i - e_j||_2}{(1 + \min(c_i, c_j))}$$

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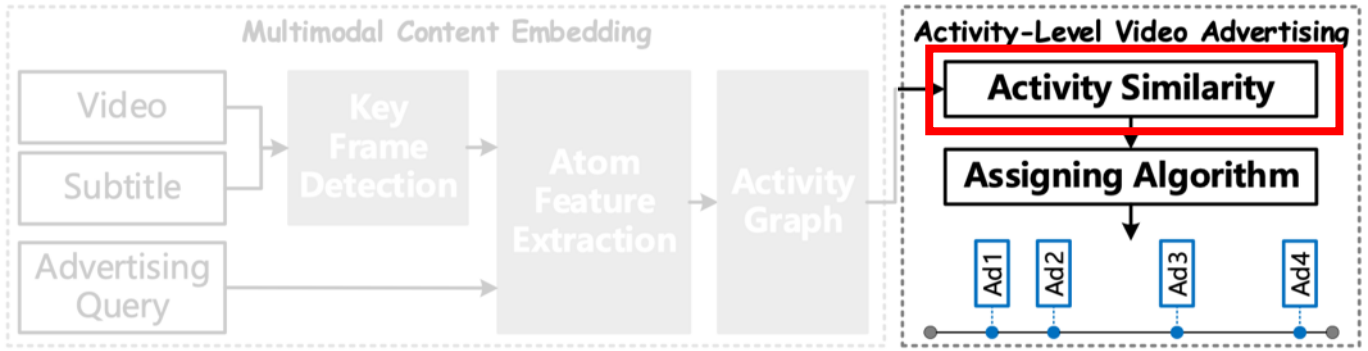
Interaction / Edge Similarity

- **Pose-Scene**
  numerical
- **Pose-Pose / Pose-Object / Pose-Face**
  categorical

$$s_3(e_i, e_j) = \begin{cases} 1 - ||e_i - e_j||_2, & \text{numerical} \\ \rho(e_i, e_j), & \text{categorical} \end{cases}$$

Activity-Level Video Advertising

Activity Similarity



Atom-Feature / Vertex Similarity

Face / Human Pose
$x = (encoding, confidence)$

$$s_1(x_1, x_2) = 1 - \frac{1}{|enc_1|} \sum_{\substack{e_i \in enc_1 \\ c_i \in conf_1}} \min_{\substack{e_j \in enc_2 \\ c_j \in conf_2}} \frac{\theta_1 ||e_i - e_j||_2}{(1 + \min(c_i, c_j))}$$

Object / Scene / Keyword

$$s_2(x_1, x_2) = \frac{1}{|cls_1|} \sum_{\substack{e_i \in cls_1 \\ c_i \in conf_1}} \max_{\substack{e_j \in cls_2 \\ c_j \in conf_2}} (\theta_2 \min(c_i, c_j) \rho(e_i, e_j))$$

$$S(g_1, g_2) = \sum w_i s_i(g_1, g_2)$$

Interaction / Edge Similarity

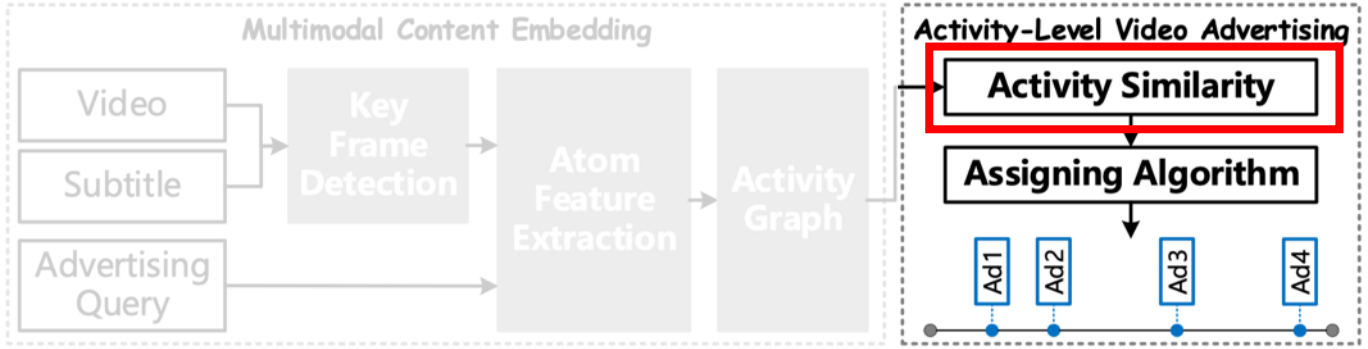
numerical

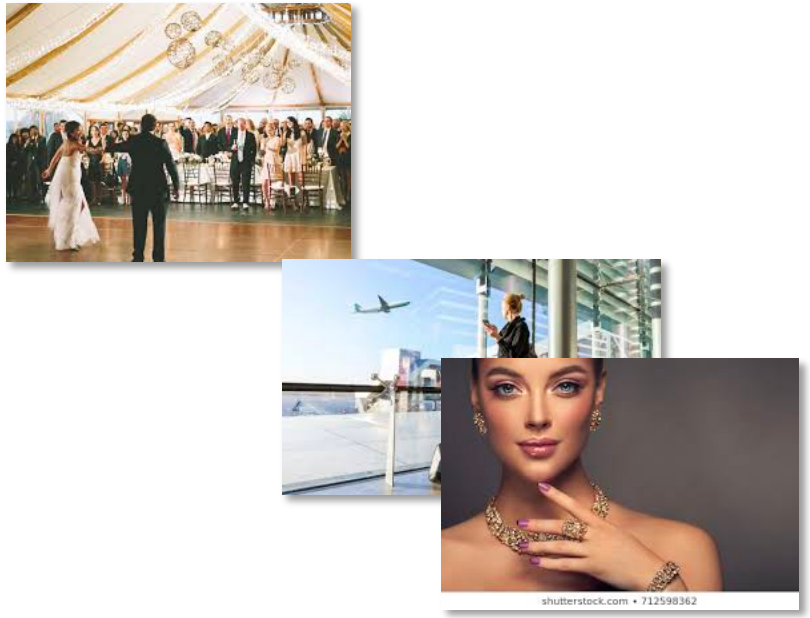
Pose-Pose / Pose-Object / Pose-Face
categorical

$$s_3(e_i, e_j) = \begin{cases} 1 - ||e_i - e_j||_2, & \text{numerical} \\ \rho(e_i, e_j), & \text{categorical} \end{cases}$$

Activity-Level Video Advertising

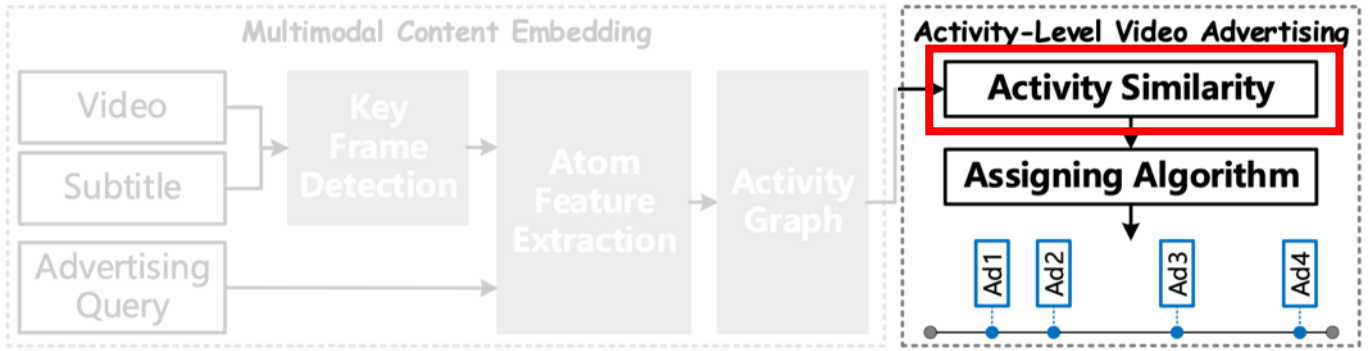
Activity Similarity





Activity-Level Video Advertising

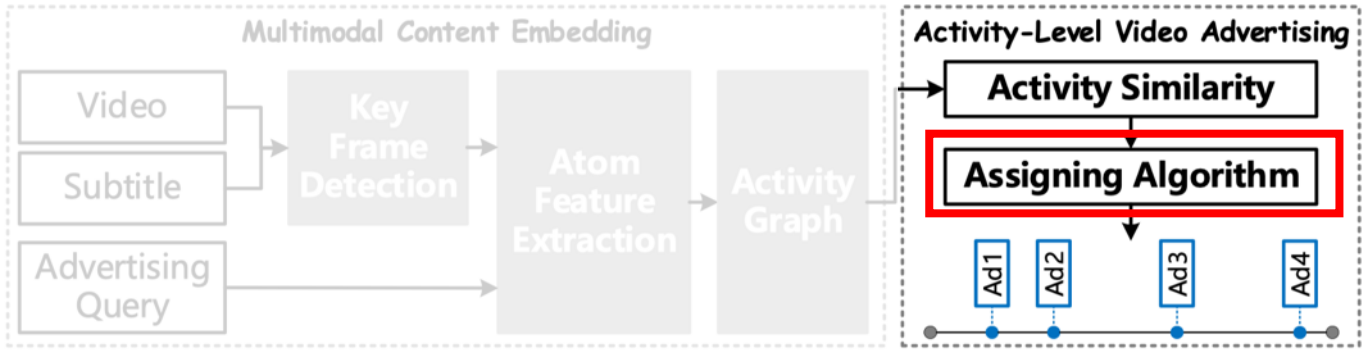
Activity Similarity



Scene: Airport

Activity-Level Video Advertising

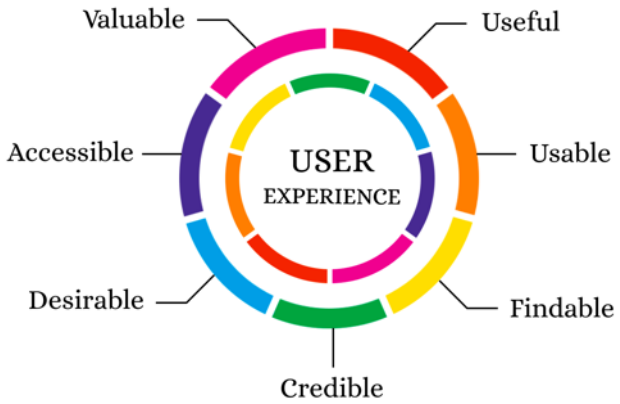
Ads Assignment



Ads Revenue

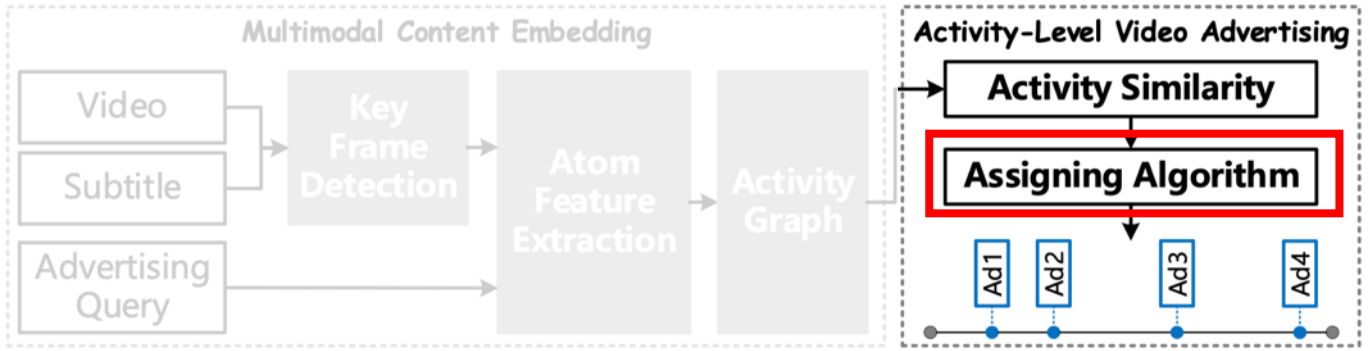
VS.

User Experience



Activity-Level Video Advertising

Ads Assignment: Ads Revenue



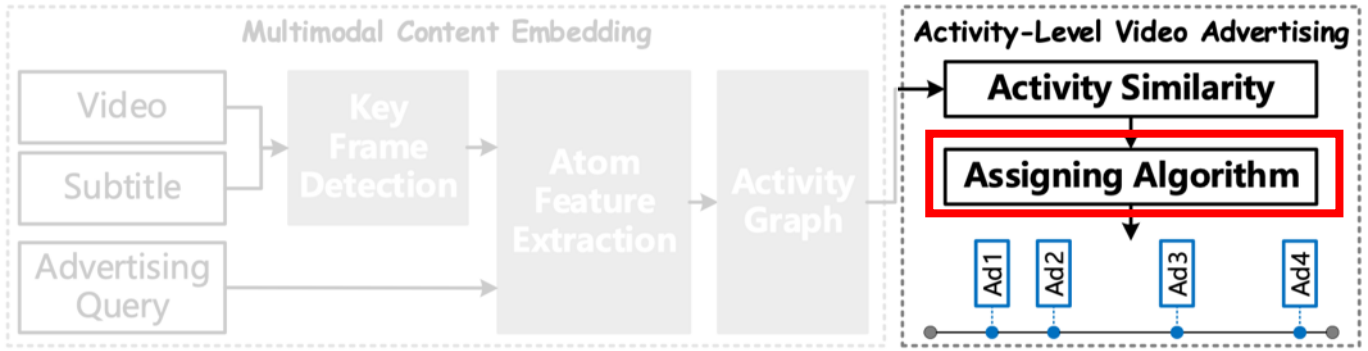
Ads Revenue

$$f(S) = \sum_{(x_i,y_j)\in S} r_j s(x_i, y_j)$$

The subset of selected ads assignments.

Activity-Level Video Advertising

Ads Assignment: Ads Revenue



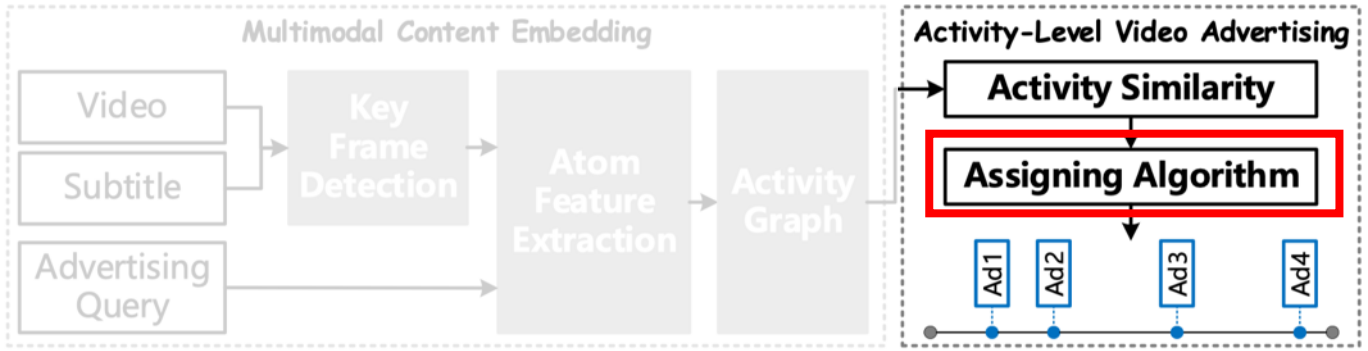
Ads Revenue

$$f(S) = \sum_{(x_i, y_j) \in S} r_j s(x_i, y_j)$$

An assignment is a pair of **key frame** and **ad query**.

Activity-Level Video Advertising

Ads Assignment: Ads Revenue



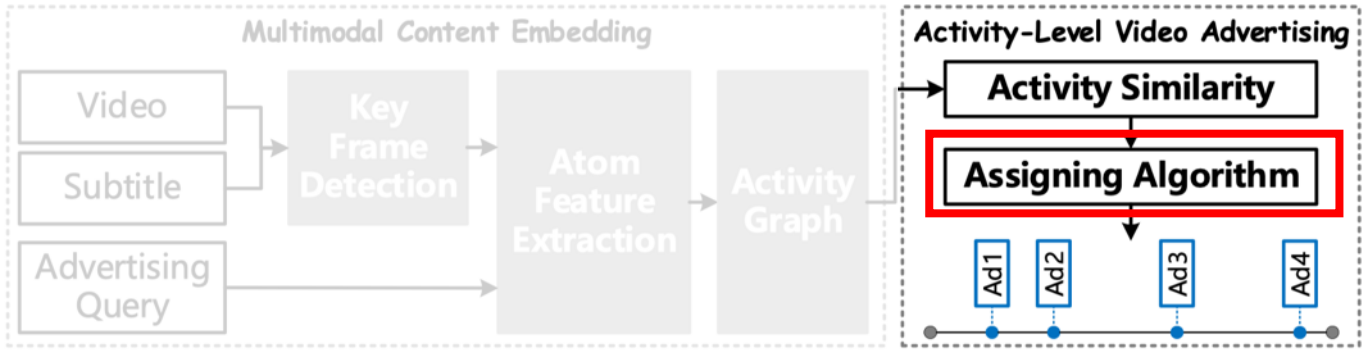
Ads Revenue

$$f(S) = \sum_{(x_i, y_j) \in S} r_j s(x_i, y_j)$$

Activity similarity between the key frame and ad query.

Activity-Level Video Advertising

Ads Assignment: Ads Revenue



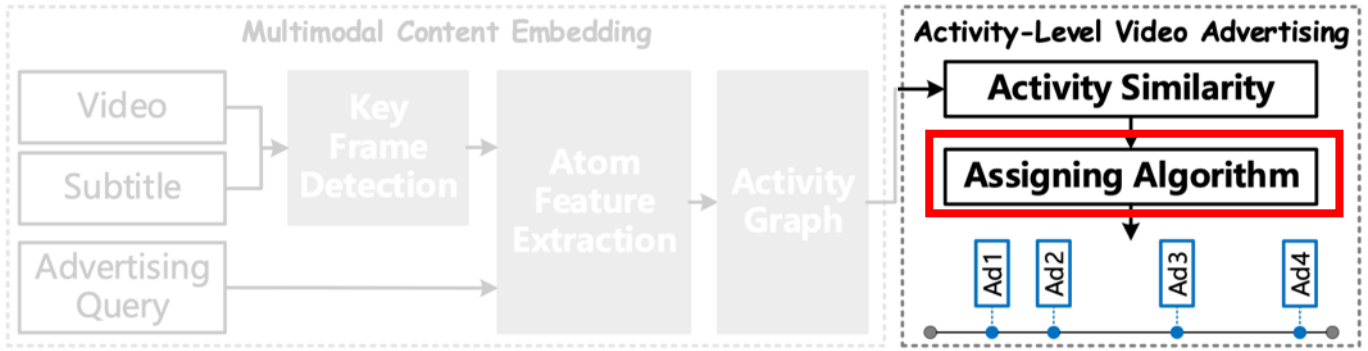
Ads Revenue

$$f(S) = \sum_{(x_i, y_j) \in S} r_j s(x_i, y_j)$$

Query-j revenue.

Activity-Level Video Advertising

Ads Assignment: Intrusiveness Perception

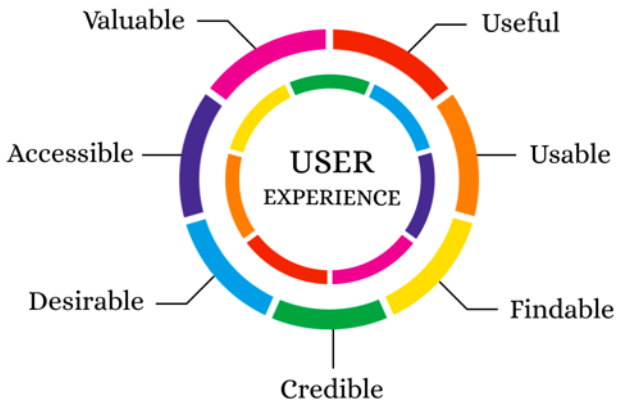


Intrusiveness Distribution Function

$$g(t|S) = 0 \quad ,0 \leq t \leq t_1$$

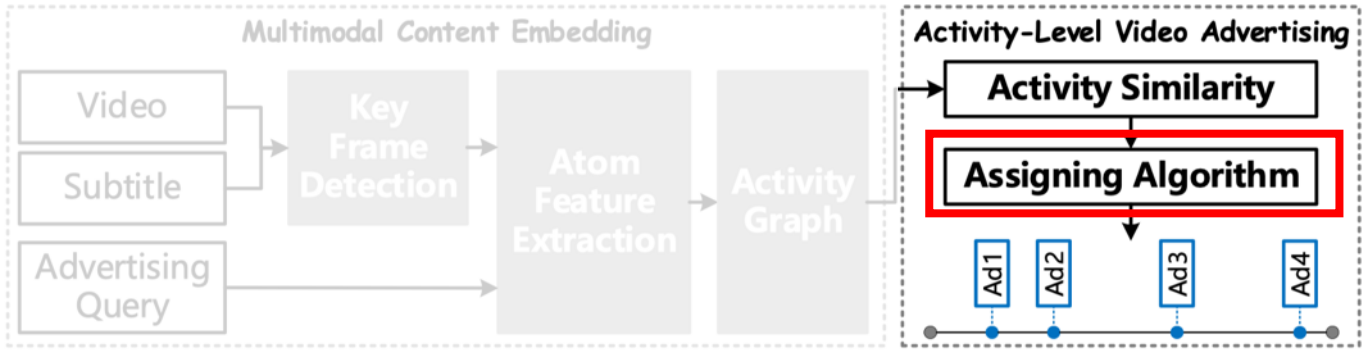
The intrusiveness of ads is the function over **viewing time** given an assigning output.

User Experience



Activity-Level Video Advertising

Ads Assignment: Intrusiveness Perception

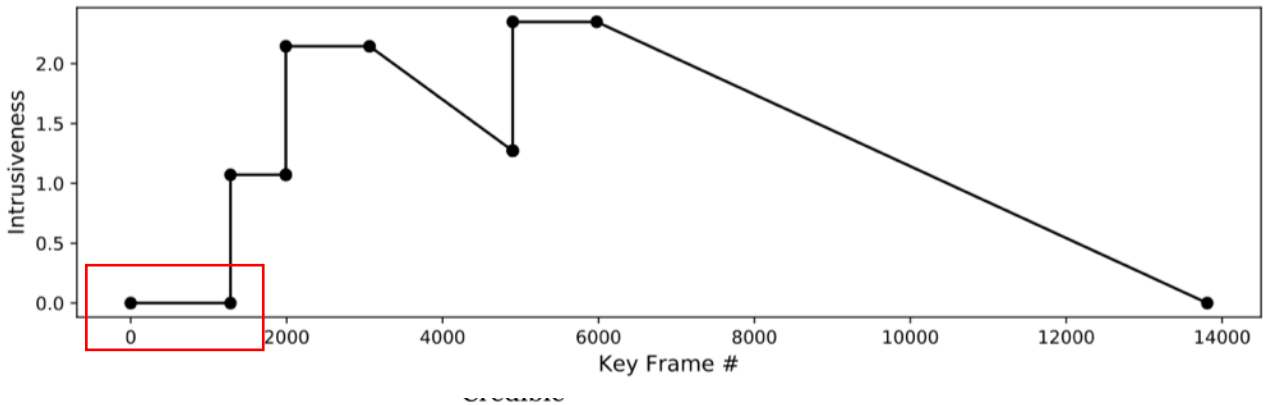


Intrusiveness Distribution Function

$$g(t|S) = 0 \quad ,0 \leq t \leq t_1$$

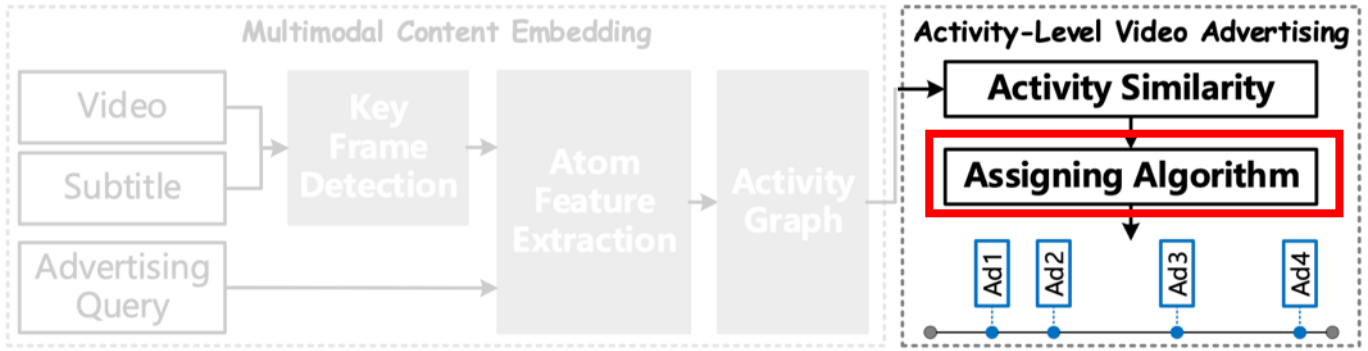
Before the first ad, the intrusiveness is 0.

User Experience



Activity-Level Video Advertising

Ads Assignment: Intrusiveness Perception



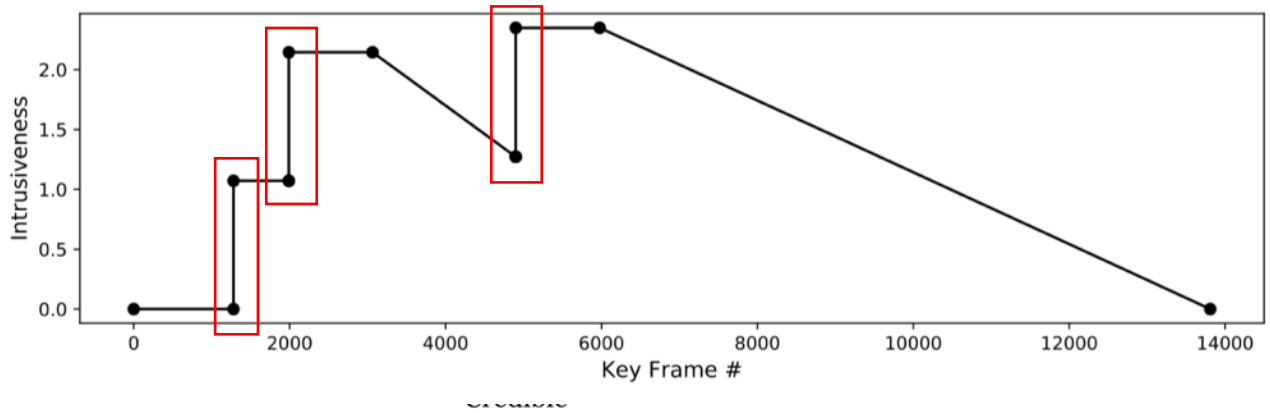
Intrusiveness Distribution Function

$$g(t|S) = 0 \quad , 0 \le t \le t_1$$

$$g(t|S) = g(t_i) + \frac{\alpha}{s(p_i)} \quad , t_i < t \le t_{i+1}$$

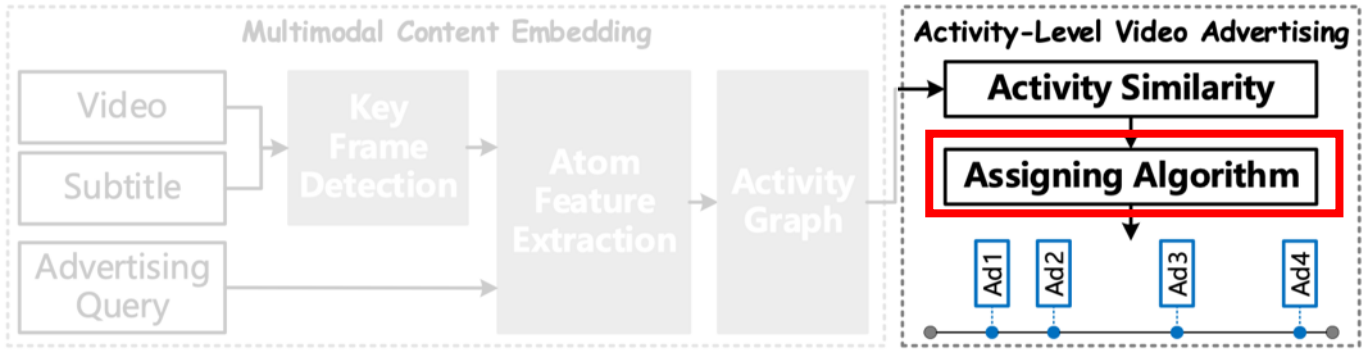
The **incremental intrusiveness** of a new ad is inversely proportional to the content similarity.

User Experience



Activity-Level Video Advertising

Ads Assignment: Intrusiveness Perception



Intrusiveness Distribution Function

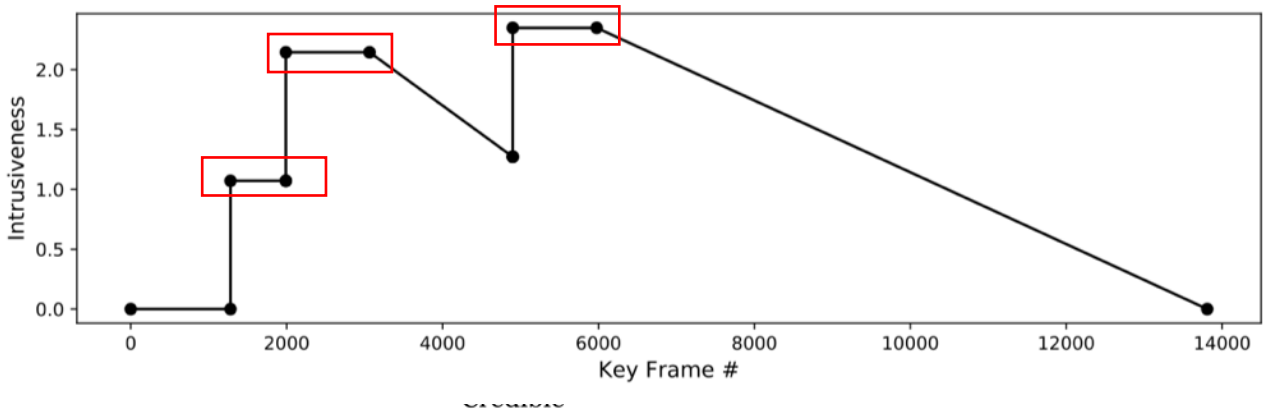
$$g(t|S) = 0 \quad , 0 \le t \le t_1$$

$$g(t|S) = g(t_i) + \frac{\alpha}{s(p_i)} \quad , t_i < t \le t_{i+1}$$

$$g(t|S) = g(t_i) + \frac{\alpha}{s(p_i)} - \gamma(t - t_i - \frac{\beta}{s(p_i)})$$

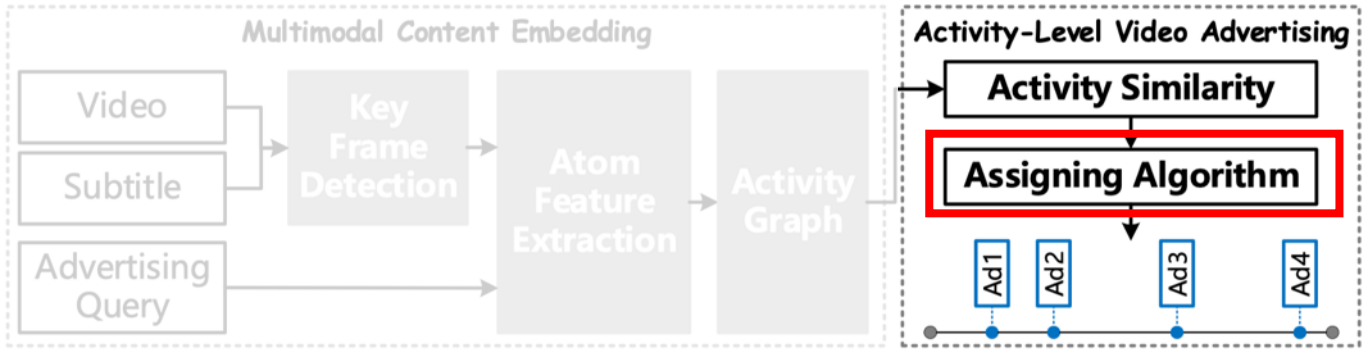
The duration of high intrusive perception is also inversely proportional to the similarity score.

User Experience



Activity-Level Video Advertising

Ads Assignment: Intrusiveness Perception



Intrusiveness Distribution Function

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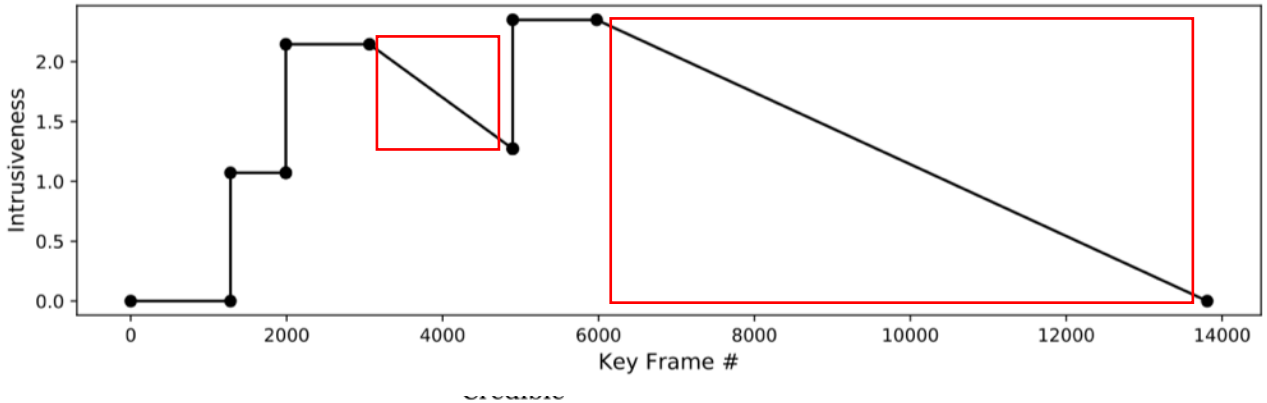
$$g(t|S) = g(t_i) + \frac{\alpha}{s(p_i)} \quad , t_i < t \le t_{i+1}$$

$$g(t|S) = g(t_i) + \frac{\alpha}{s(p_i)} - \gamma(t - t_i - \frac{\beta}{s(p_i)})$$

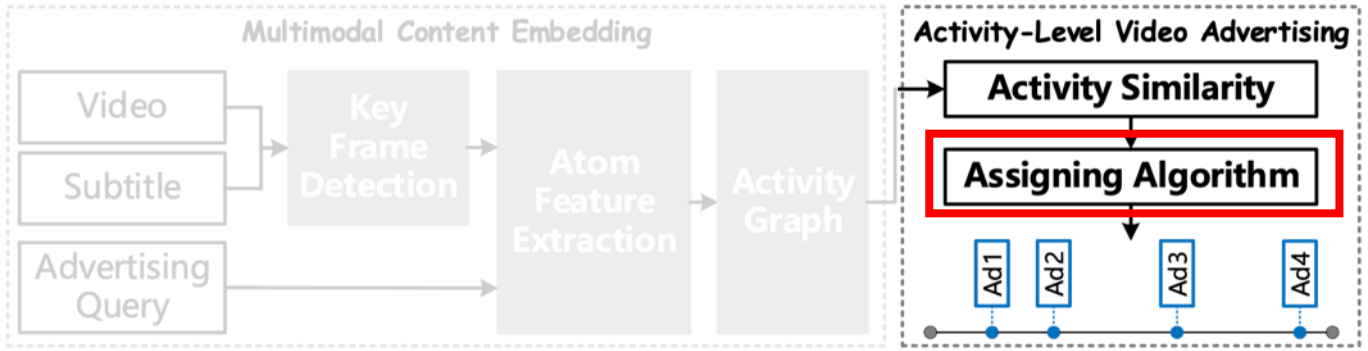
As the time goes on, the intrusiveness will decline and γ controls the descent speed.

User Experience



Activity-Level Video Advertising

Ads Assignment: Trade-Off Model



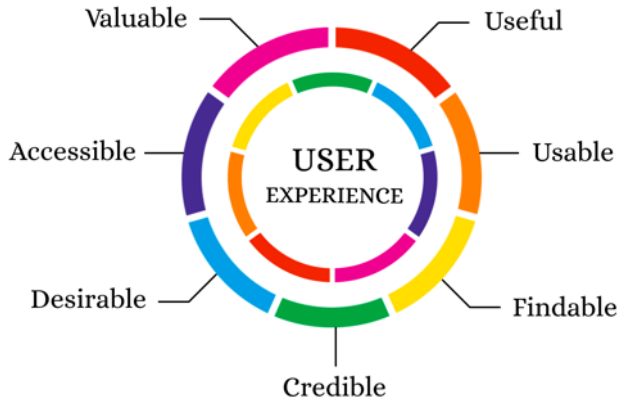
Ads Revenue

Trade-Off Model: Revenue Optimization under Intrusiveness Constraint

$$\max_{S \subseteq P} f(S) + \delta E(S)$$

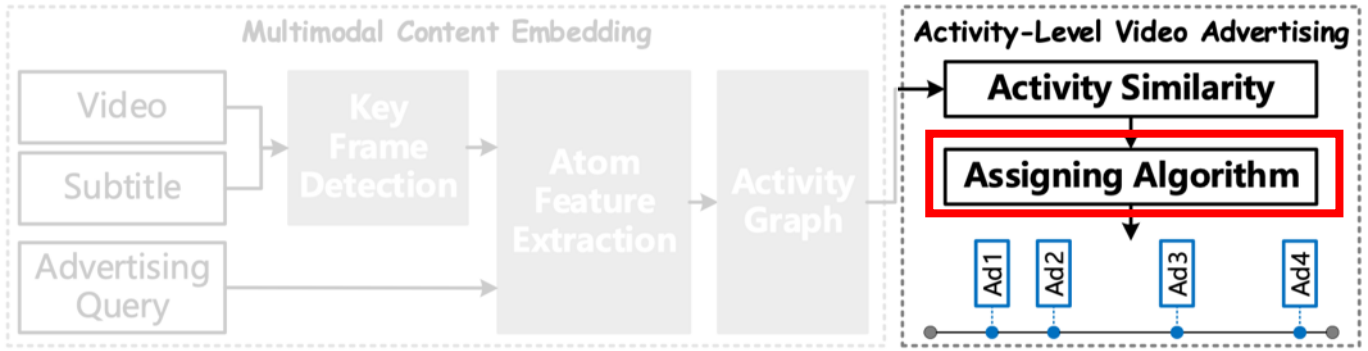
$$\text{s.t.} \quad \int_0^{t_{max}} g(t|S)\mathrm{d}t \leq B$$

User Experience



Activity-Level Video Advertising

Ads Assignment: Trade-Off Model



Ads Revenue

$$E(S) = -\sum_{(x_i,y_j)\in S} p_{y_j} \log_2 \frac{p_{y_j}}{N_y}$$

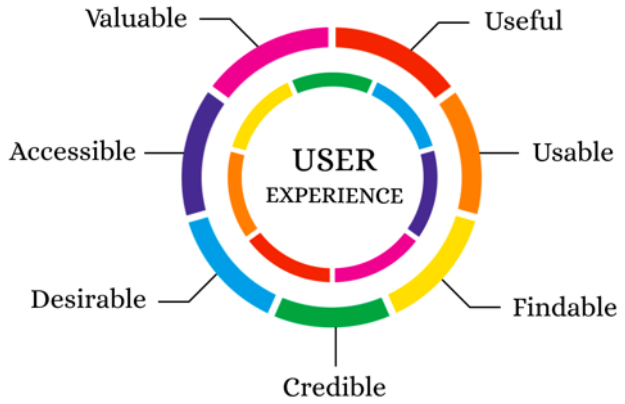
Trade-Off Model: Revenue Optimization under Intrusiveness Constraint

$$\max_{S\subseteq P} f(S) + \delta E(S)$$

$$\text{s.t.} \quad \int_0^{t_{max}} g(t|S)\mathrm{d}t \le B$$

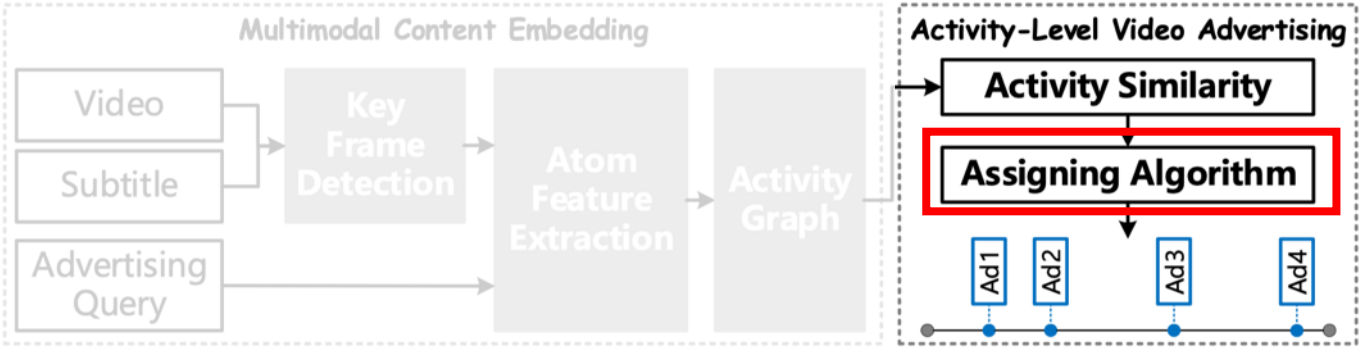
E(S) is an entropy-like function that measures balance of served ad queries distribution.

User Experience



Activity-Level Video Advertising

Ads Assignment: NMS-Greedy Algorithm



Trade-Off Model:
Revenue Optimization under Intrusiveness Constraint

$$\max_{S \subseteq P} f(S) + \delta E(S)$$

$$\text{s.t.} \quad \int_0^{t_{max}} g(t|S)\mathrm{d}t \leq B$$

Algorithm 1 NMS-Greedy algorithm for Equation 9.

Require: key frame set X, ad set Y, intrusiveness budget B
Ensure: assignments S

1: Initialize the value matrix $M_{N_y \times N_x}$, where $m_{ij} = r_i s(x_j, y_i)$.
2: Apply the kernel $K_{11 \times N_x}$ to M.
3: Apply the kernel $K_{2 N_y \times N_k}$ to M.
4: Greedily select assignments with $\arg\max m_{ij}$ into S until $\int_0^{t_{max}} g(t|S)\mathrm{d}t$ exceeds the intrusiveness budget B.
5: **return** S

Activity-Level Video Advertising

Ads Assignment: NMS-Greedy Algorithm

Algorithm 1 NMS-Greedy algorithm for Equation 9.

Require: key frame set X, ad set Y, intrusiveness budget B
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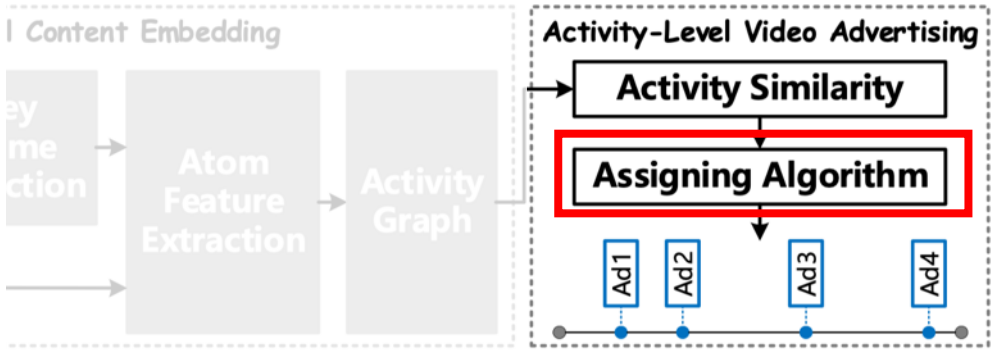
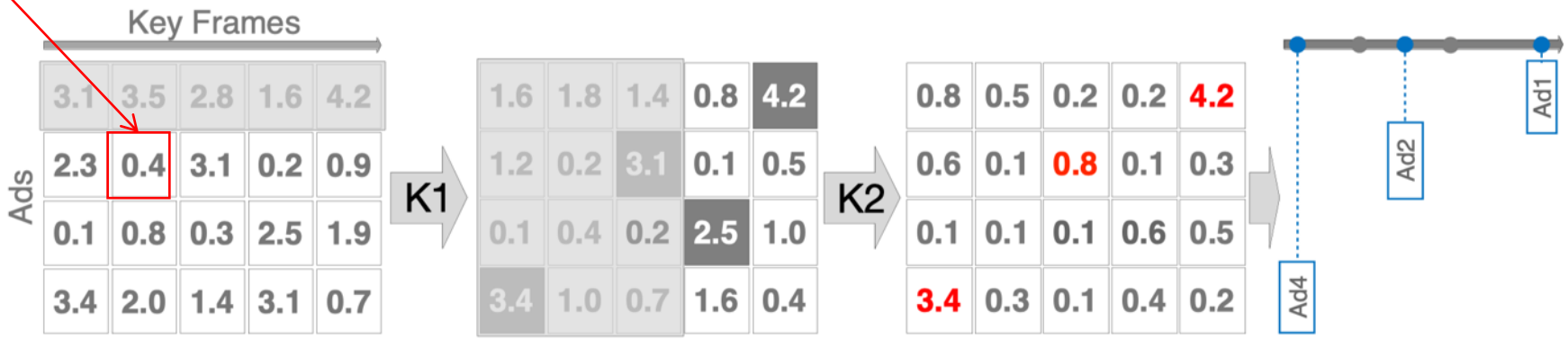
5: **return** S





Calculating the pairwise similarity to construct the value matrix.

Activity-Level Video Advertising

Ads Assignment: NMS-Greedy Algorithm

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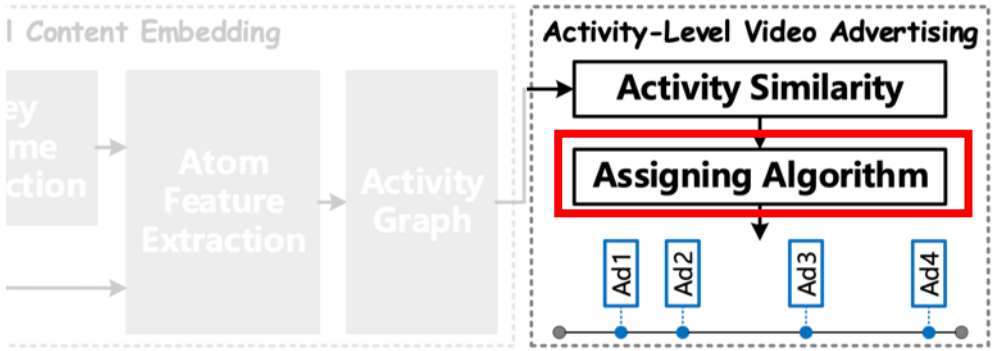
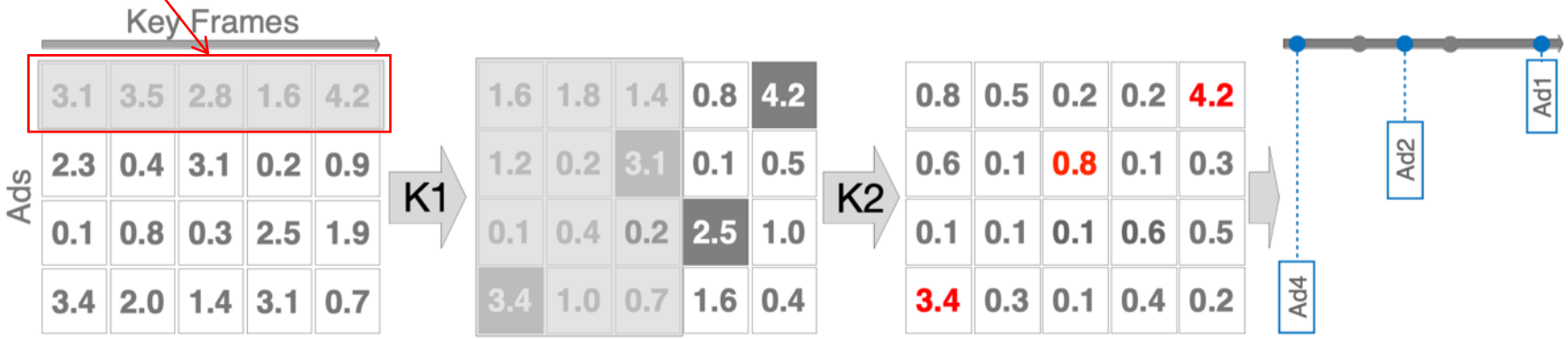
5: **return** S



K1: Balancing the assignments for each ad.



Activity-Level Video Advertising

Ads Assignment: NMS-Greedy Algorithm

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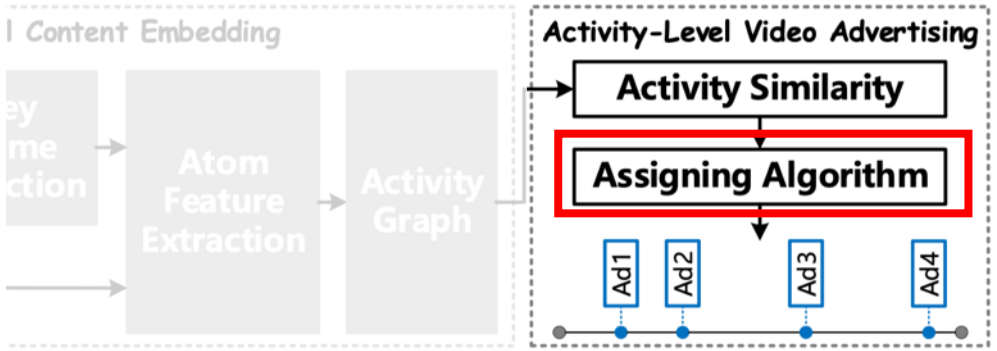
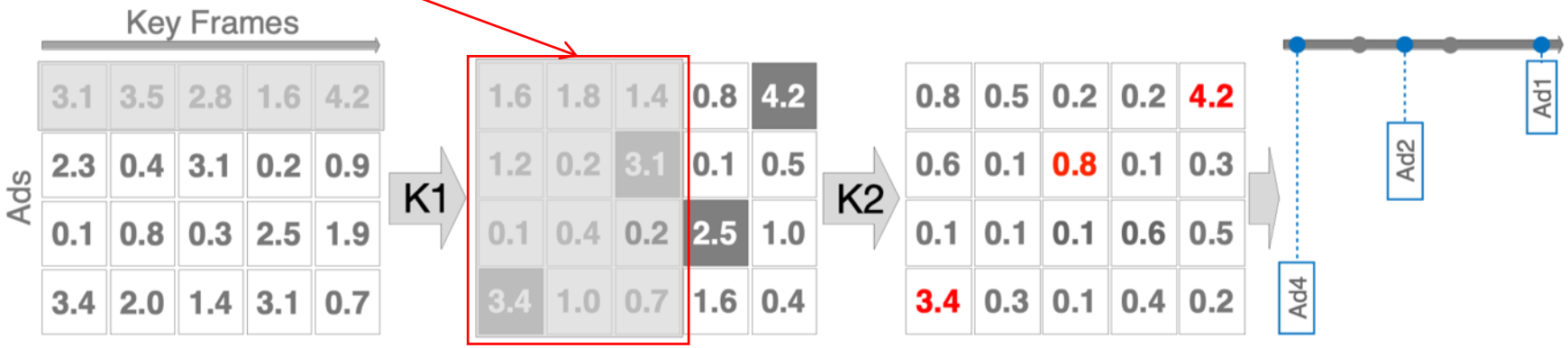
4: Greedily select assignments with $\arg\max m_{ij}$ into S until $\int_0^{t_{max}} g(t|S)\mathrm{d}t$ exceeds the intrusiveness budget B.
5: **return** S





K2: Avoiding successive ads within short interval.

Activity-Level Video Advertising

Ads Assignment: NMS-Greedy Algorithm

Algorithm 1 NMS-Greedy algorithm for Equation 9.

Require: key frame set X, ad set Y, intrusiveness budget B
Ensure: assignments S

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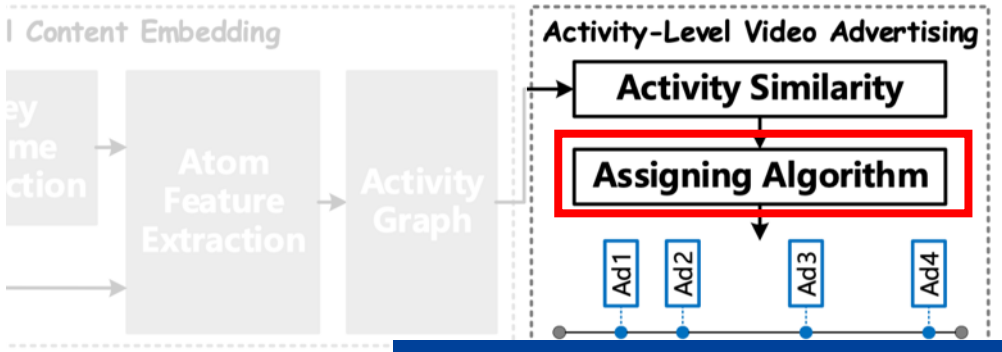
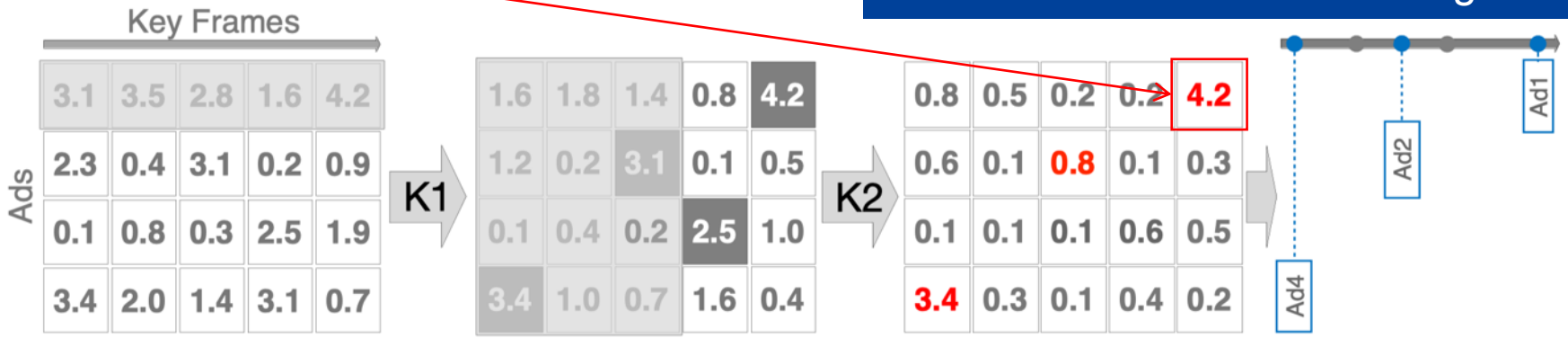
2: Apply the kernel $K_{1 1 \times N_x}$ to M.
3: Apply the kernel $K_{2 N_y \times N_k}$ to M.
4: Greedily select assignments with $\arg\max m_{ij}$ into S until $\int_0^{t_{max}} g(t|S)\mathrm{d}t$ exceeds the intrusiveness budget B.
5: **return** S

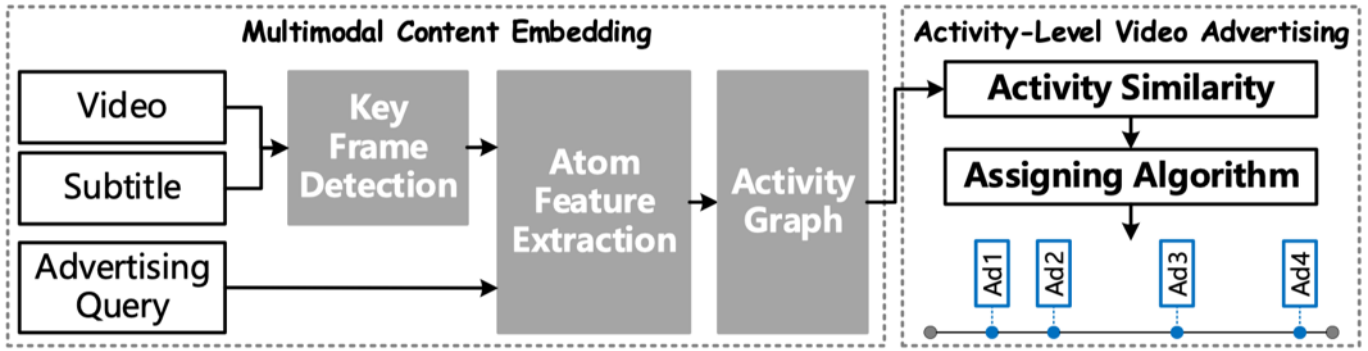


Greedy assigning ads until reaching intrusiveness budget.



Activity-Level Video Advertising

ActVA: Extensibility

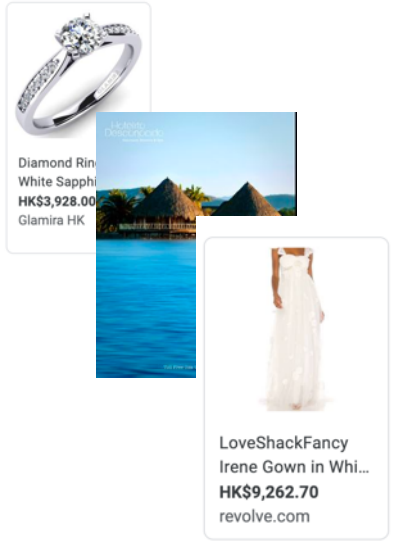


No need for activity-level labelled training data.

Video Data

&

Ads Query



→ **Activity Graph Representation**

Outline

- Introduction
- Multimodal Content Embedding
- Activity-Level Video Advertising
- **Evaluation**
- Conclusion

Evaluation

Experiment Setup

140 Videos

100X

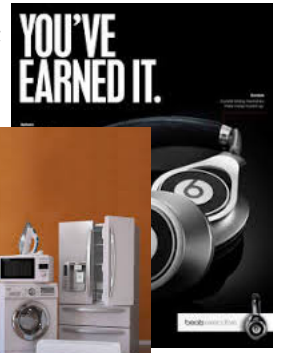
10X

30X

150 Real Ads Needs

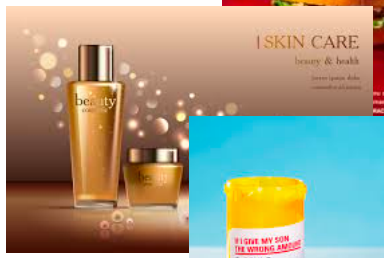
Vehicle

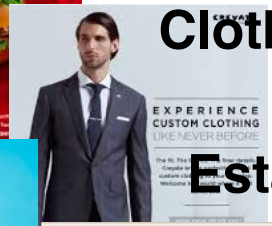
Electronic



Food and Beverage

Cosmetic

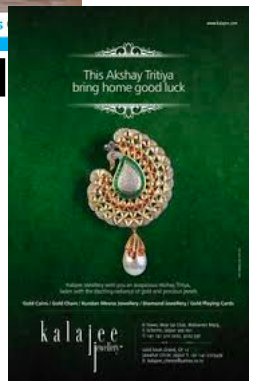




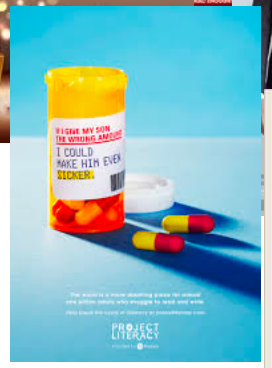
Clothing

Estate

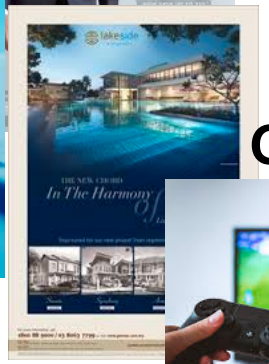
Household



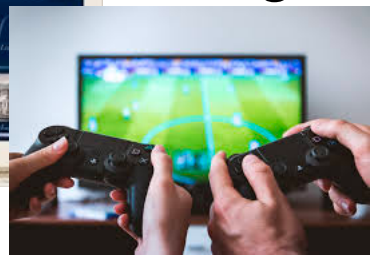
Jewelry



Medicine

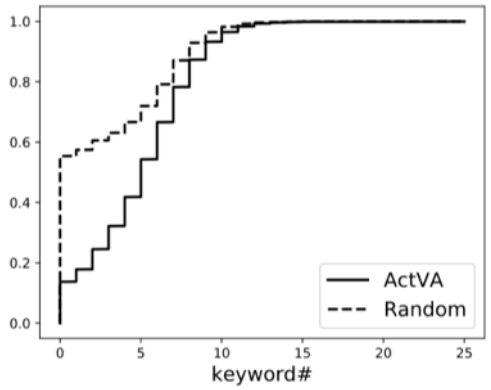


Gaming

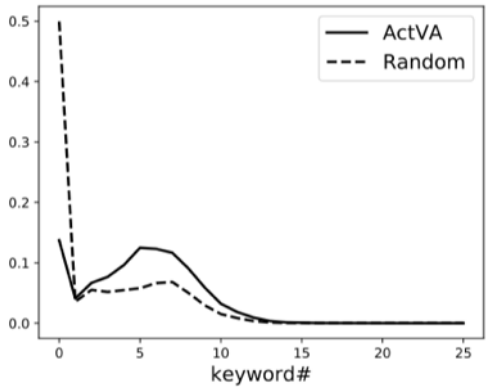


Evaluation

Semantic-Shot Key Frame Detection



(a) Keyword# CDF.



(b) Keyword# distribution.

Richer Textual Information

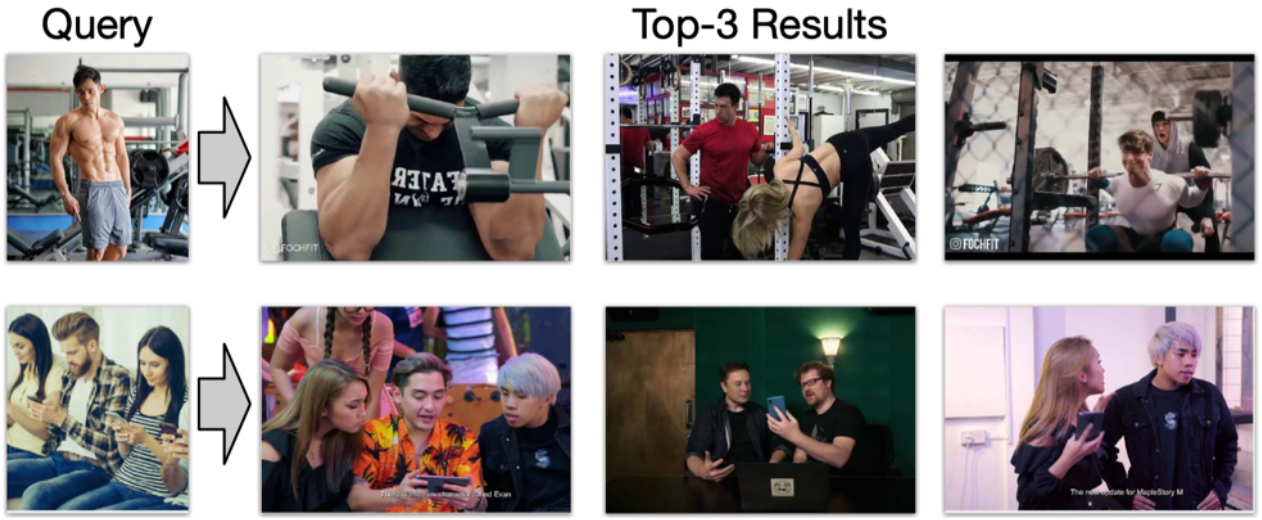
High Accuracy with >10k FPS retrieval speed

Evaluation

Advertising Position Retrieval

(a) Keyword# CDF.

(b) Keyword# distribution.

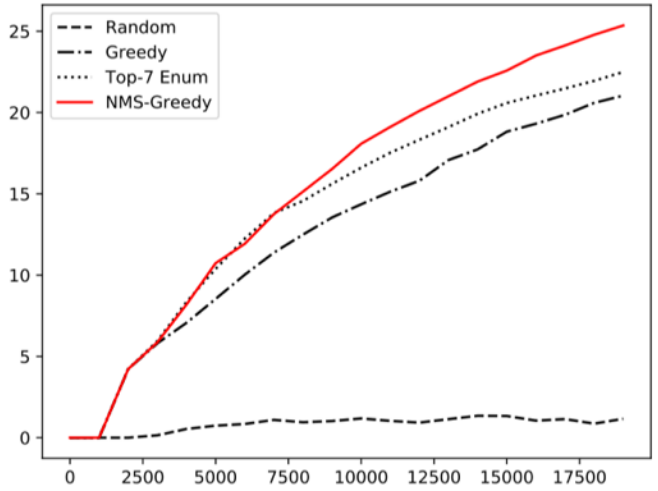


Richer Textual Information

High Accuracy with >10k FPS retrieval speed

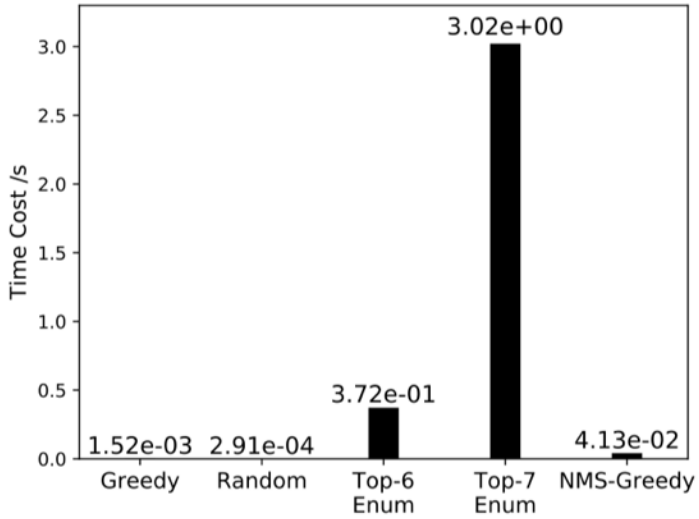
Evaluation

NMS-Greedy Ads Assignment



(a) Average Assignment Value V.S. Intrusiveness Budget

Highest Value



(b) Average Time Cost

Low Cost

(c) Subject Intrusiveness Evaluation

User Friendly

Evaluation

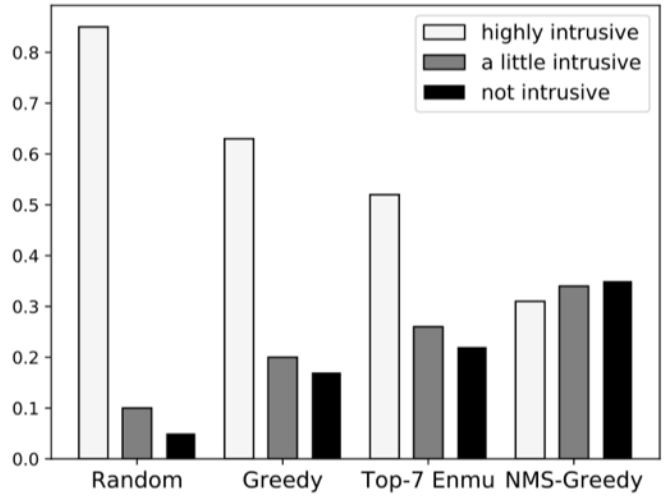
NMS-Greedy Ads Assignment

(a) Average Assignment Value V.S. Intrusiveness Budget

Highest Value

(b) Average Time Cost

Low Cost



(c) Subject Intrusiveness Evaluation

User Friendly

Outline

- Introduction
- Multimodal Content Embedding
- Activity-Level Video Advertising
- Evaluation
- **Conclusion**

Take-Home Message

Based on **atom features** and **activity-graph representation**, we can implement an efficient and scalable activity-level video advertising system.

Lab for Intelligent Networking & Knowledge Engineering

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CCF Dist Speaker
Wireless Network
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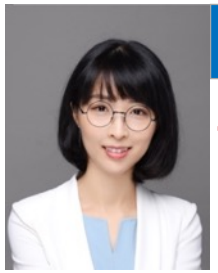
USA NYU A.P.
CPS, Algorithms,
Distributed optimization
Machine learning



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CCF, ACM China Doctor Thesis Award, Youqing Qingcheng Award
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Privacy Protection

Bei Hua

High-Performance Computing
Edge Computing

Yu Zhang

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Quantum software

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Wireless Network Resource Management

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IEEE Fellow
Prof. in Rutgers
NSF Career

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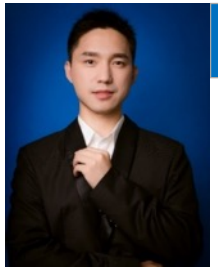
Cloud Computing
Algorithms Analysis

YuBo Yan

Wireless/Passive Network, IntelliSense, IoT, SDR



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Passive Network
Theories of Information and Coding

Xin Guo

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