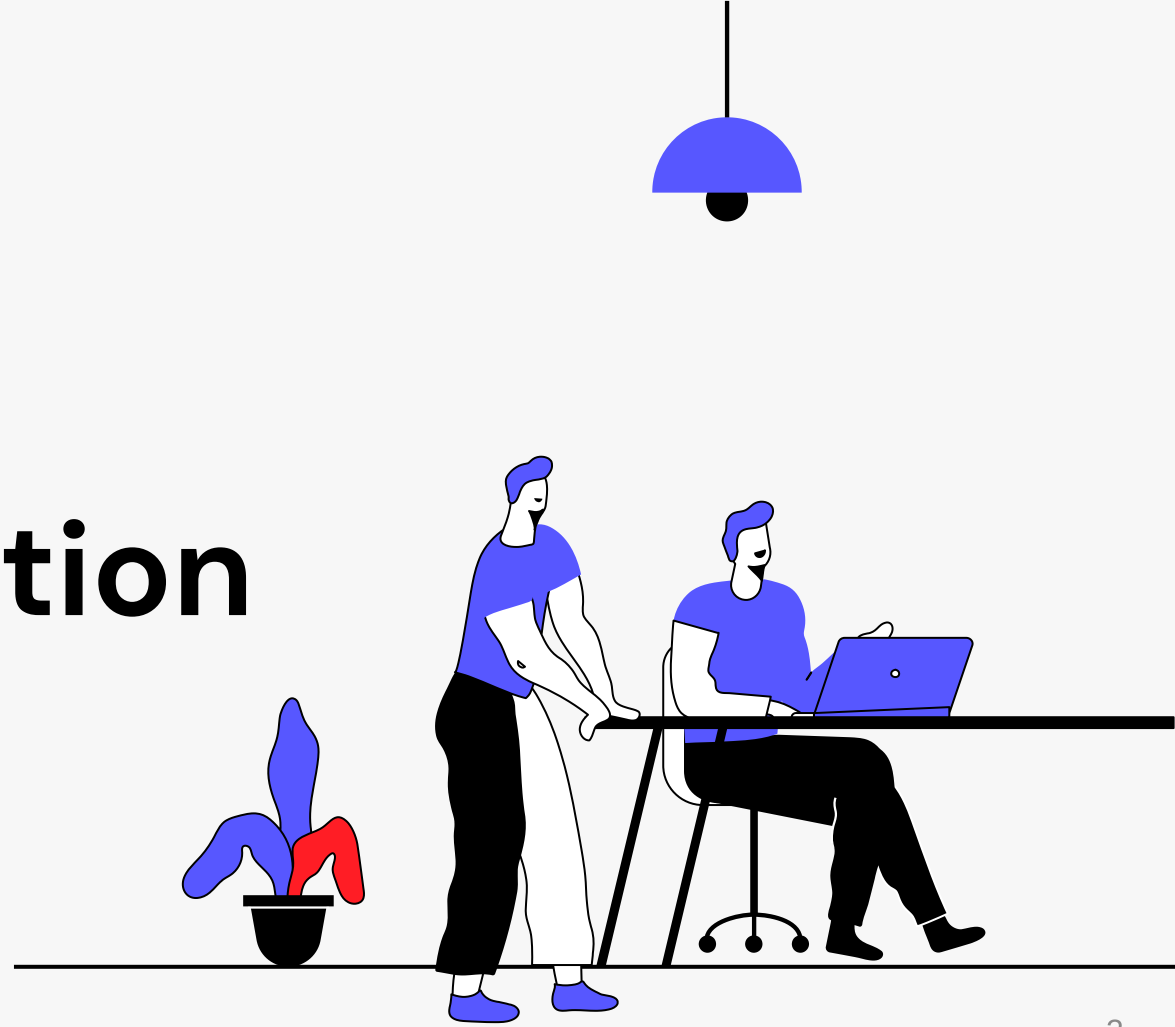
Is Your Guest an Ally Or an Enemy? Predicting Cannibalization Effects of Featured Videos on Social Media Platforms

Advisor: Chih-Ping Wei, Ph.D.
Presenter: Ching-Yao Lin

Department of Information Management, National Taiwan University. July, 2023

01

Introduction



01 – Background

Social media applications (social apps) have become more important than ever

Customer Side

60%

World's population uses social media[1]

2h24'

World's average daily usage[1]

72.8%

Internet users use it for brand research[1]

> 50%

US customers open it on a daily basis (Deloitte, 2016)

Business Side

81%

Orgs raise brand awareness with social media[1]

71%

B2C orgs report that they will be engaging in influencer marketing[1]

$16.4B

Global influencer marketing market value (2x since 2019)[2]

> "Social platforms serve as an effective tool helping companies with their marketing strategies and goals, such as CRM and CI (Alalwan et al., 2017)"

[1] Datareportal (2023). https://datareportal.com/reports/digital-2023-april-global-statshot
[2] Statista (2023). https://www.statista.com/topics/2496/influence-marketing/#topicOverview

01 – Background

Video streaming platforms play a significant part in these social apps

Customer Side

50%

US customers subscribe to video streaming services (Deloitte, 2016)

91.8%

Internet users watch online video content weekly[1]

"Users spend significantly more time on video-based platforms than other social apps, with TikTok and YouTube ranked as the top two platforms in terms of time spent on social apps[1]"

Business Side

80.5%

B2B decision makers use it for work-related purchase research

16.3%

B2B decision makers say video sites influences their ultimate purchase decision

75%

Marketers use YouTubers in their marketing strategy

$6.5

Earned for every $1 spent (Average ROI) for YouTube influencer marketing

[1] Datareportal (2023). https://datareportal.com/reports/digital-2023-april-global-statshot
[2] Ginux (2023). https://blog.gitnux.com/youtube-influencer-marketing-statistics/

01 – Background

Influencer marketing is a lucrative business on social video streaming platforms

$6B

YouTube influencer marketing market value (Deloitte, 2016)

$187.5K

Average amount charged by YouTubers per sponsored video (BBC, 2016)

$100–250K

Average amount charged by TikTokers per sponsored video (Forbes, 2022)

Social media influencers on video streaming platforms maximize their income by enhancing popularity

- Influencers are paid according to their popularity, which is often measured by the total number of subscribers or followers, or the number of views in the past few videos

01 – Motivation

- Collaboration between influencers help grow their channels, but not always

Collaboration between influencers is a prominent strategy to increase popularity on social video streaming platforms

- To increase earnings, influencers collaborate with each other to expose their videos to a broader audience and thereby to increase video views (Koch et al., 2018)
- The rationale is that, after B is featured as a guest in A’s video, the viewers of A are more likely to watch B’s videos and even become subscribers
- This often happens reciprocally to expand channels on both sides (Koch et al., 2018)

01 – Motivation

- Example of featured videos

01 – Motivation

- Collaboration between influencers may help grow their channels, but not always

However, such collaborations are not always beneficial to both sides

- Cannibalization can cause unintended harm to a social media business when pursuing such a collaboration strategy
- In this study, cannibalization is said to occur when the popularity of the host channel dropped significantly after collaborating with the invited guest influencer
- Building upon the previous example, it is possible that followers of an influencer A are attracted to another influencer B to the extent that it significantly reduces A’s popularity, measured by a nose-dive in total views or watch time. This undoubtedly goes against the original intention of collaborating with B.
- In the data we collected, 3.3% of featured videos are labeled as cannibalized

01 – Motivation

- Cannibalization prediction deserves research effort

Cannibalization is a risk that should be identified and prevented in advance

- If we can predict cannibalization before a decision on featuring another channel, we can avoid harmful collaborations that would in turn compromise the popularity and value of a influencer’s channel

However, cannibalization prediction was not explored in extant research

- Cannibalization is poorly identified in existing work and relevant discussion often is limited to the context of products
- To the best of our knowledge, the cannibalistic effect is nowhere investigated in the context of collaborations among social media influencers
- Accordingly, there is no similar prediction task in the past on identifying cannibalization, including that of featured videos in social media platforms

01 – Objectives

- Define a cannibalization prediction problem and propose a method to resolve it

We define cannibalization in the context of featured videos within social apps and a prediction task to identify such phenomenon in advance

- Our goal is to predict the occurrence of such unintended outcome, given the current state of channels and videos from both sides. This supports the decision on whether a host influencer should collaborate with a guest influencer.

To this end, we propose a DNN method to tackle this prominent problem

- We collected a dataset of featured videos and their relevant data to investigate this problem
- We aim to establish several plausible benchmarks, and utilize cross-validation to evaluate our model

02

Literature Review

02 – Traditional Definition of Cannibalization

There isn't a generally agreed-upon definition of cannibalization

- "The process by which a new product gains sales by diverting sales from an existing product" (Heskett et al., 1976)
- "The extent to which one product's sales are at the expense of other products offered by the same firm" (Copulsky et al., 1976)
- "'Redistributed' revenue, in that existing buyers are substituting one item for another in the company's product portfolio" (Kerin et al., 1978)

Novelli (2013) offered a detailed definition of cannibalization after summarizing most frequently cited definitions

- "The intra-organizational phenomenon of sales diversion by means of which sales of a product or service (the cannibal) are generated by diverting potential sales that a substitute product or service (the victim) would have obtained in absence of the former, ceteris paribus, within a common organizational realm collecting the revenues of both"

02 – Traditional Definition of Cannibalization

Status quo of existing definitions of cannibalization

- Most cited definitions are based on cannibalization among products within a company. They did not consider cannibalization during a brand alliance, where brands typically come from different companies
- Also, current definitions describe the general phenomenon, but the concept is still vague and there isn't a standard measurement to gauge cannibalization

Three things are needed to clear the ambiguity in current definitions

- Draw a clear contrast between cannibalization among products and that among brands
- Identify standard measurements for distinct types of cannibalization
- Characterize each type of cannibalization with clear-cut standards

02 – Traditional Definition of Cannibalization

First, it must be clear that cannibalization can be divided into two main categories.

- Product Cannibalization: caused by different products from the same company
  - One product takes away a portion of the market share or revenue stream from another existing product
- Co-branding Cannibalization: caused by co-branding, or brand alliances, typically involving two or more companies
  - Brand alliances (Co-branding): “two or more existing brands are combined into a joint product or are marketed together in some fashion” (Keller, 2013)
  - One brand cannibalizes another brand after their collaboration by placing both in the same marketing context, such as an advertisement, a promotion, or a joint product

02 – Traditional Definition of Cannibalization

Second, cannibalization can be measured in various ways.

- Product cannibalization is typically measured by sales volume or sales value, in the form of either changes in absolute value or in (relative) market share
- Co-branding cannibalization can be measured by Sales-based Brand Equity (SBBE) and Consumer-based Brand Equity (CBBE)

1. SBBE: A decrease in monetary value of a brand (typically evaluated through revenue changes)
2. CBBE: A denigration of customers' perception toward a brand (typically assessed via customer surveys)

02 – Cannibalization in Social Platform Featured Videos

Cannibalization in the context of featured videos in social apps is closer to co-branding cannibalization

- We can view influencers as different brands and videos as their products
- A collaboration between influencers can be regarded as brand alliance, and therefore a featured video can be regarded as a co-branding joint product
- Influencers may cannibalize each other by stealing popularity, which is often measured with the number of subscribers or total video views, both of which can serve as proxies for the followers' preference or perception

02 – Cannibalization in Social Platform Featured Videos

Our operational definition of cannibalization is given as "a significant percentage drop in host channel's total video views of *k* videos after a certain featured video, as compared to that of *k* videos before that featured video"

- We adopt total videos views, instead of subscriber count, as our measurement of cannibalization due to two reasons
  - Subscriber count is not a practical measurement because it generally rarely goes down. Followers who do not like an influencer anymore can just simply stop clicking into his or her videos, and soon the recommendation system of the social platform will stop showing relevant videos
  - Total video views naturally reflects the popularity of an influencer in real time. Besides, Watching a video is analogous to consumption of a product. The more the consumption, the higher the popularity.

03

Proposed Method

03 – Problem Formulation

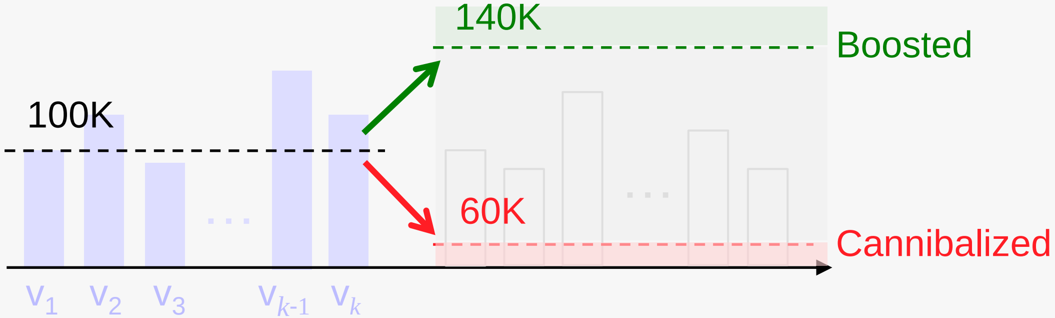
- Our task is a 3-class classification problem given past data of host and guest channels

Given the below:

- Channel features from both sides (host and guests)
- Features of host's past k videos prior to a given featured video
- Features of guests' past k videos prior to a given featured video

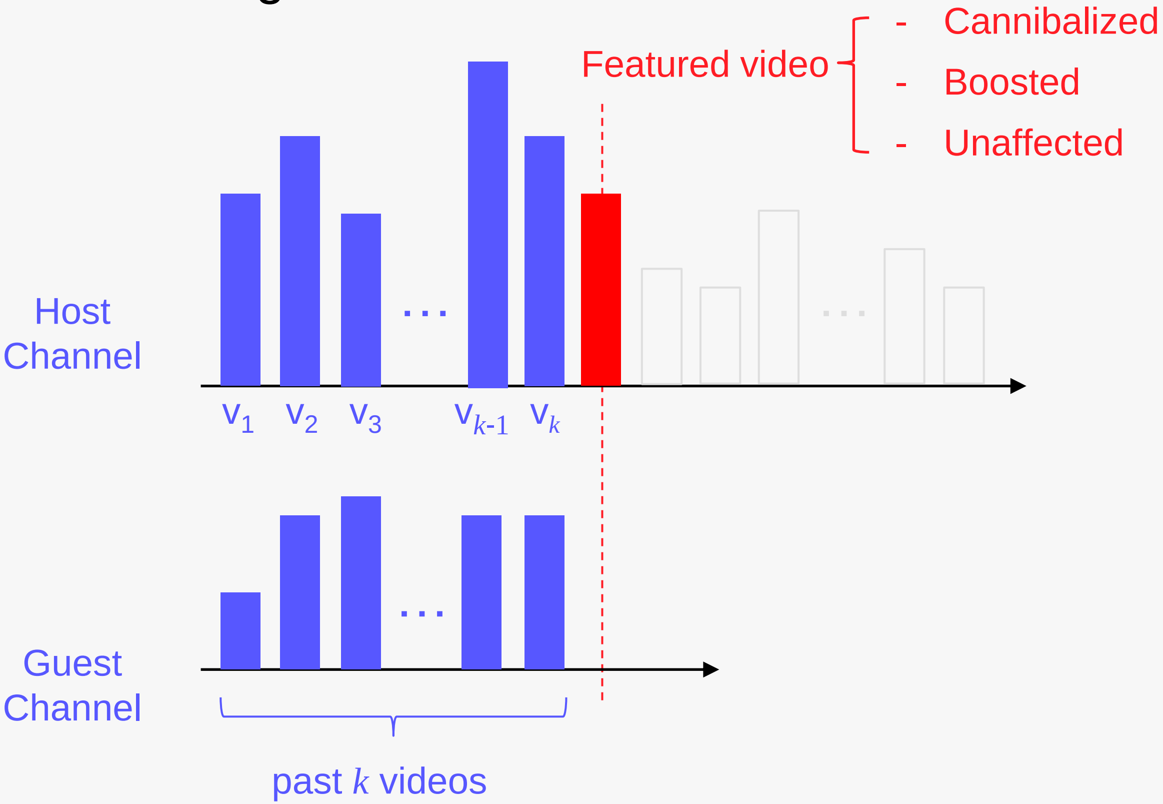
Our task is to predict whether a given featured video is:

- Cannibalized: The views of host's next k videos dropped θ %
- Boosted: The views of host's next k videos rose θ %
- Unaffected: The views of host's next k videos did not change over θ %



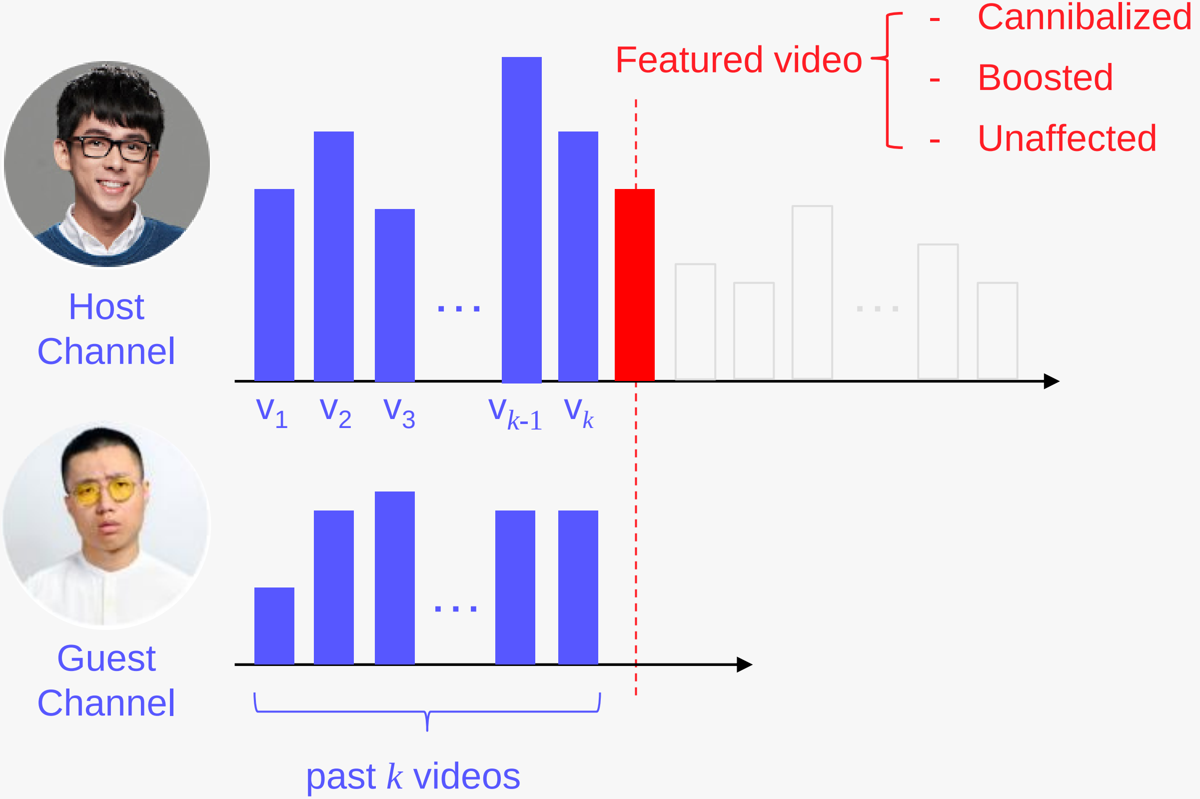
03 – Problem Formulation

- Our task is a 3-class classification problem given past data of host and guest channels



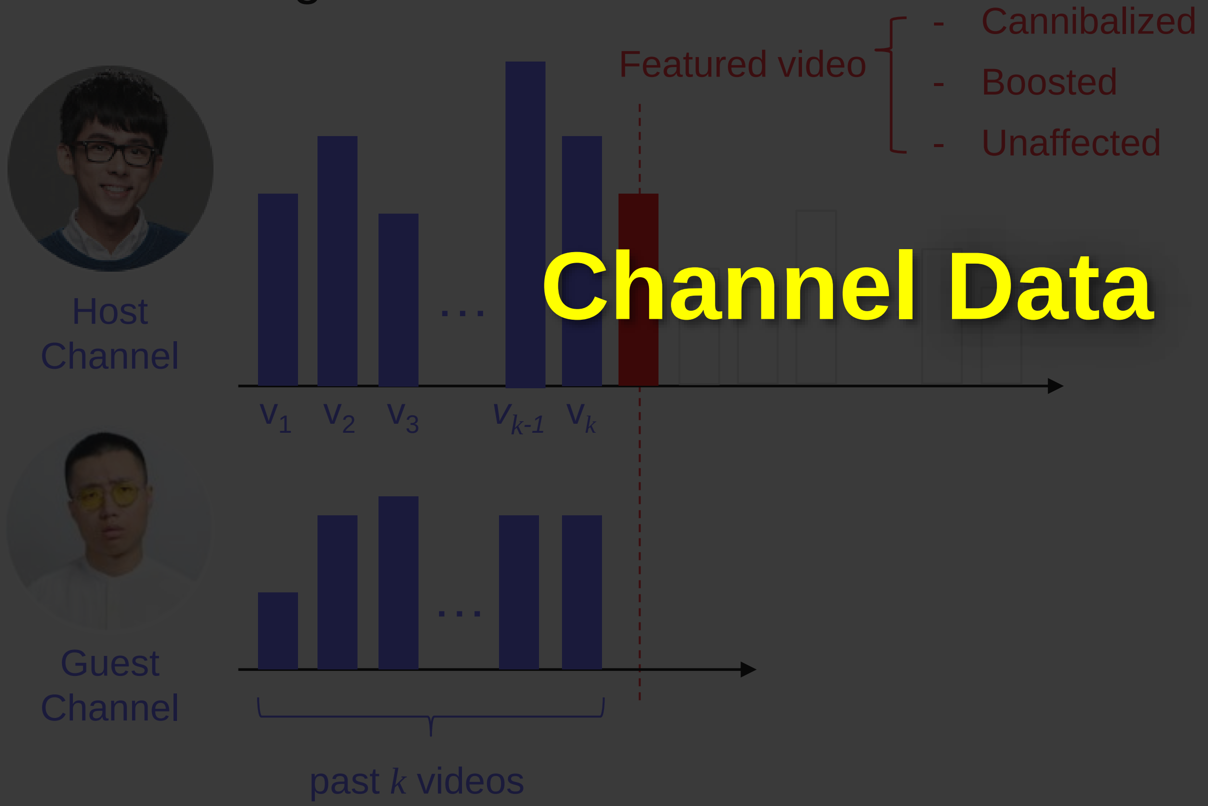
03 – Problem Formulation

- Our task is a 3-class classification problem given past data of host and guest channels



03 – Problem Formulation

- Our task is a 3-class classification problem given past data of host and guest channels



03 – Problem

- Our task is a 3-class cla…
host and guest channels

Host Channel

03 – Problem

- Our task is a 3-class cla...
host and guest channels

Title
Description
Keywords

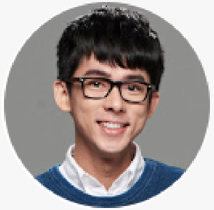
Text

#Subscribers
#Videos
#TotalViews
PublishDate

Statistics

Topic Categories

Category



Host
Channel

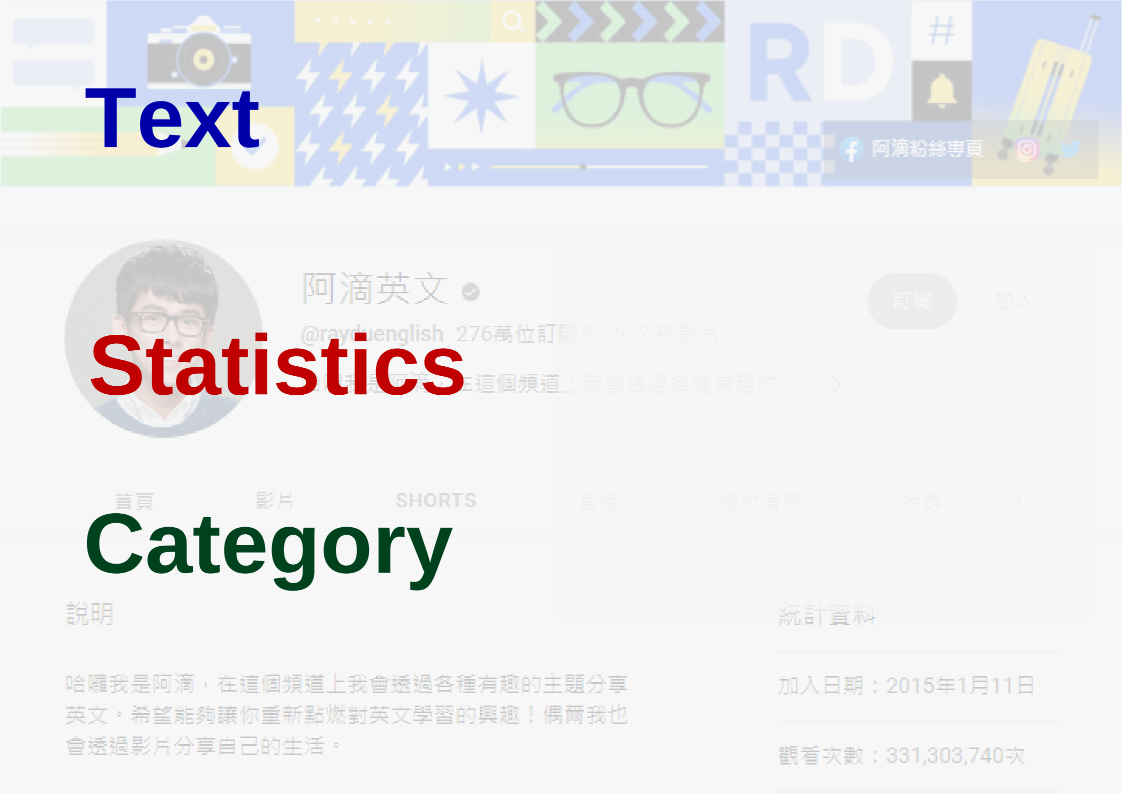
Guest
Channel

Fea...

V_1 V_2 V_3 V_{k-1} V_k

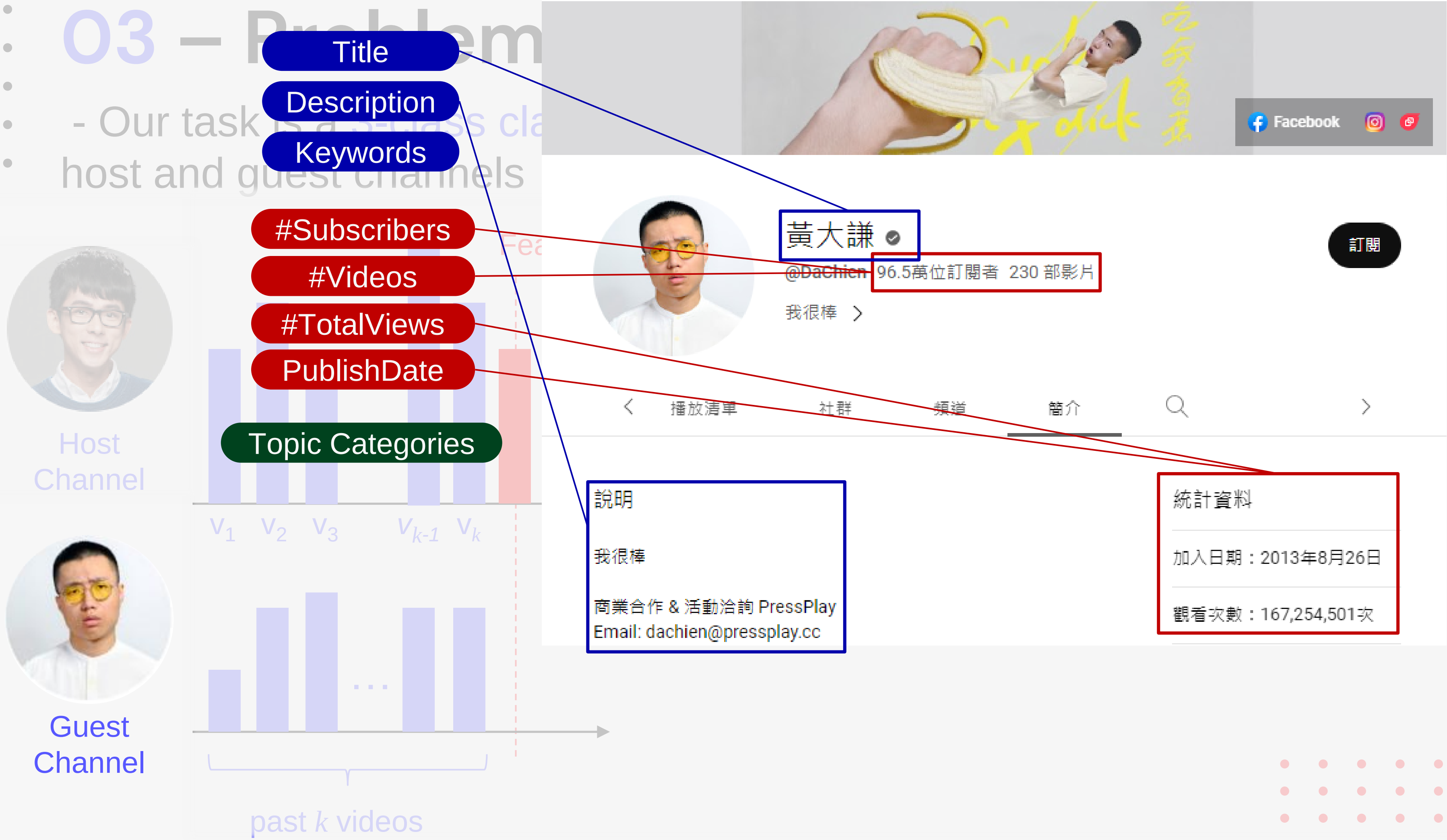
…

past k videos



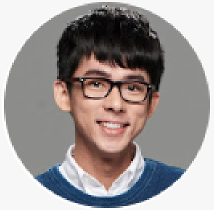
03 – Problem

- Our task is a 3-class cla... host and guest channels



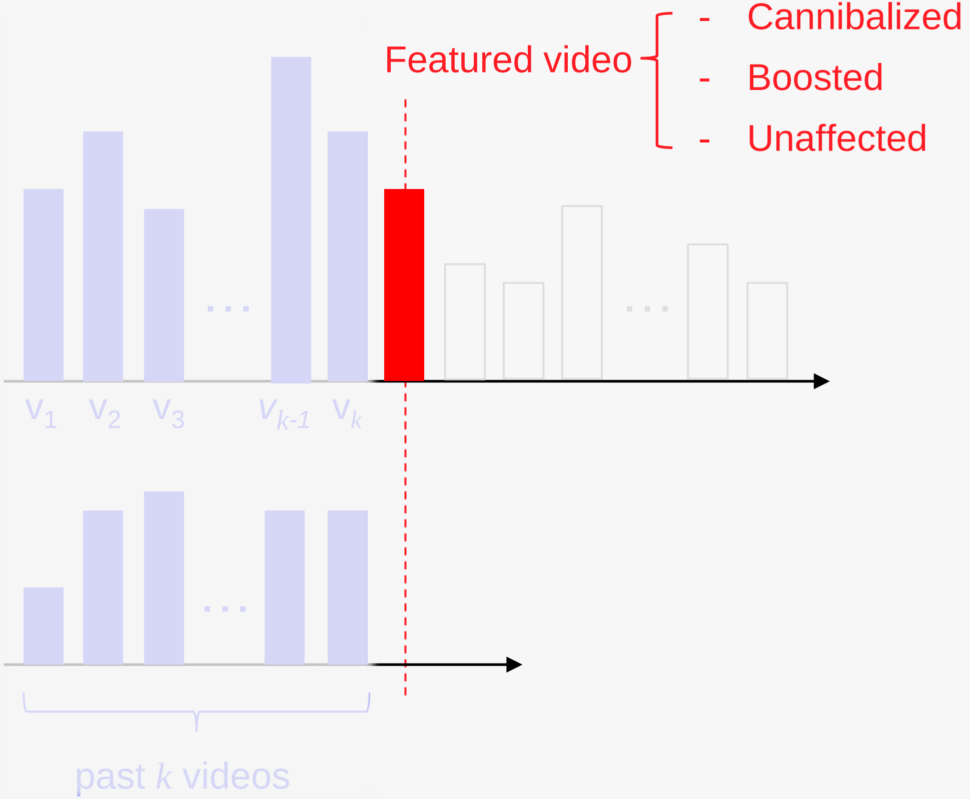
03 – Problem Formulation

- Our task is a 3-class classification problem given past data of host and guest channels



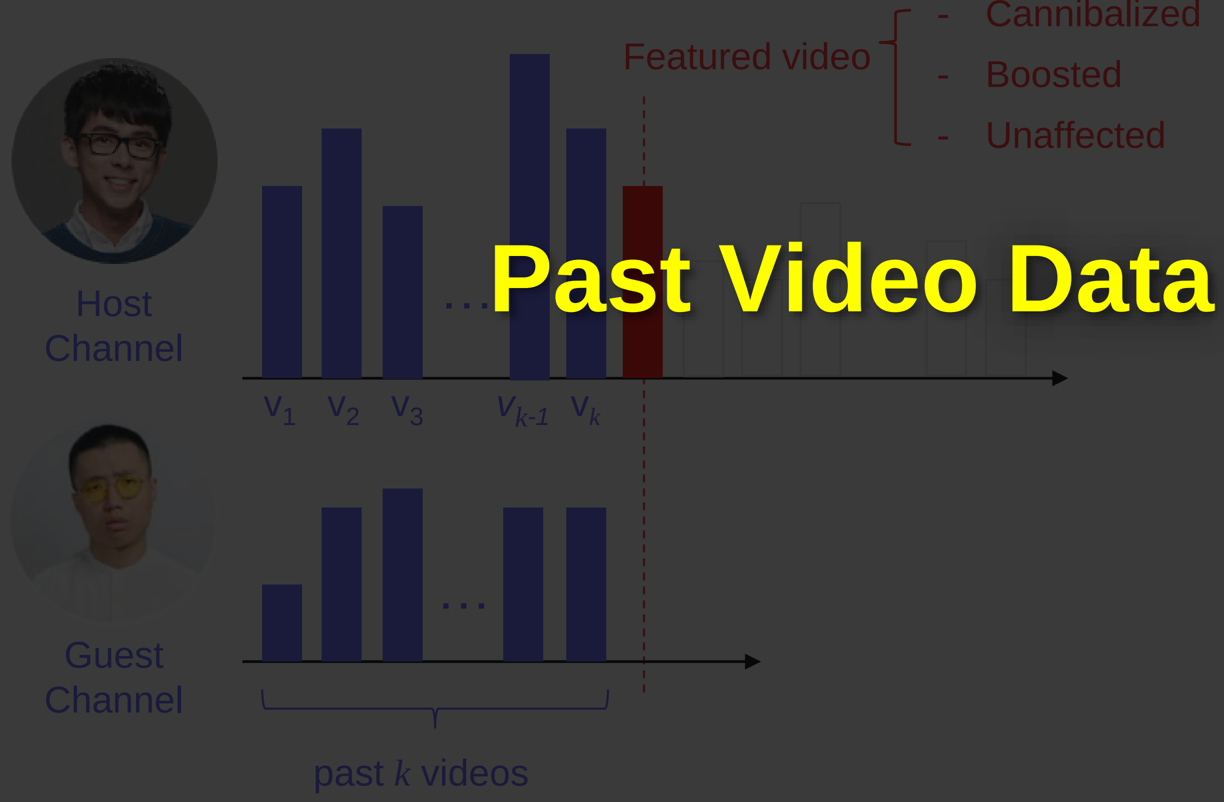
Host Channel

Guest Channel



03 – Problem Formulation

- Our task is a 3-class classification problem given past data of host and guest channels



03 – Problem F

- Our task is a 3-class classif
host and guest channels

Title

Description

Tags

Duration

#Views

#Likes

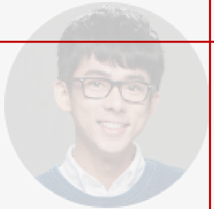
#Comments

PublishDate

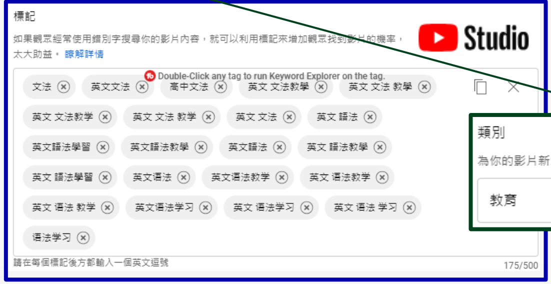
Category

Featured

Host Channel



V_1 V_2 V_3 … V_{k-1} V_k



Text

- Title
- Description
- Tags

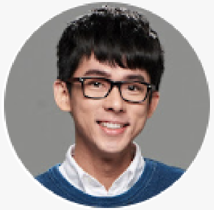
Statistics

- Duration
- #Views
- #Likes
- #Comments
- PublishDate

Category

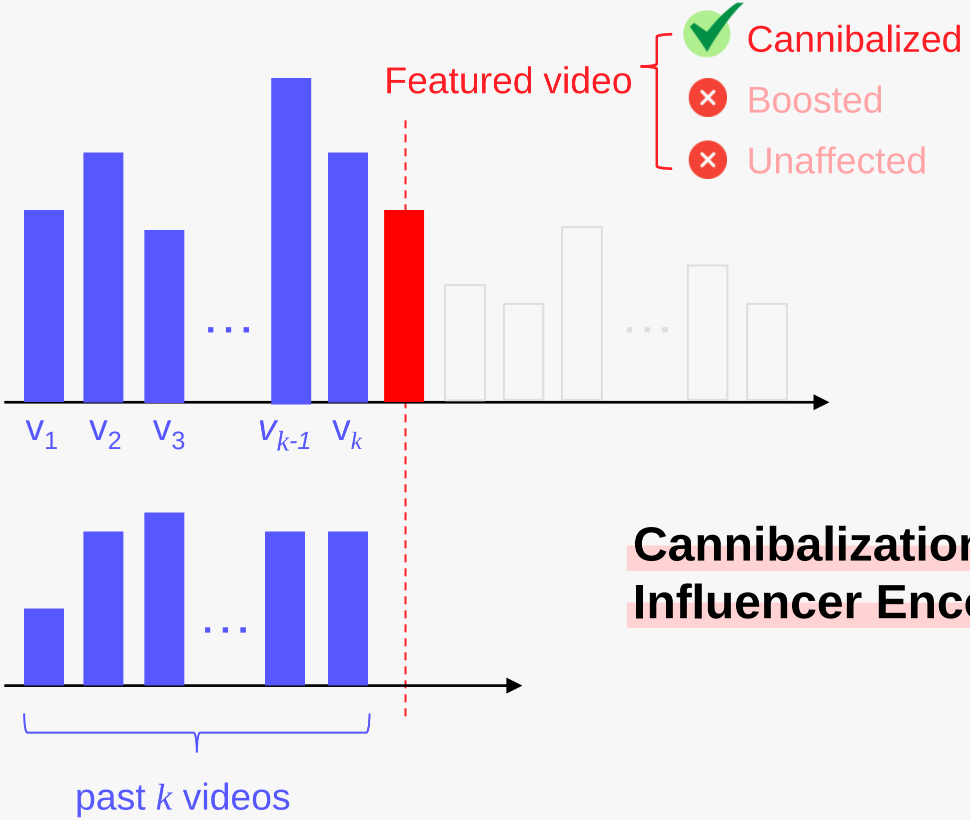
- Category

03 – Problem Formulation



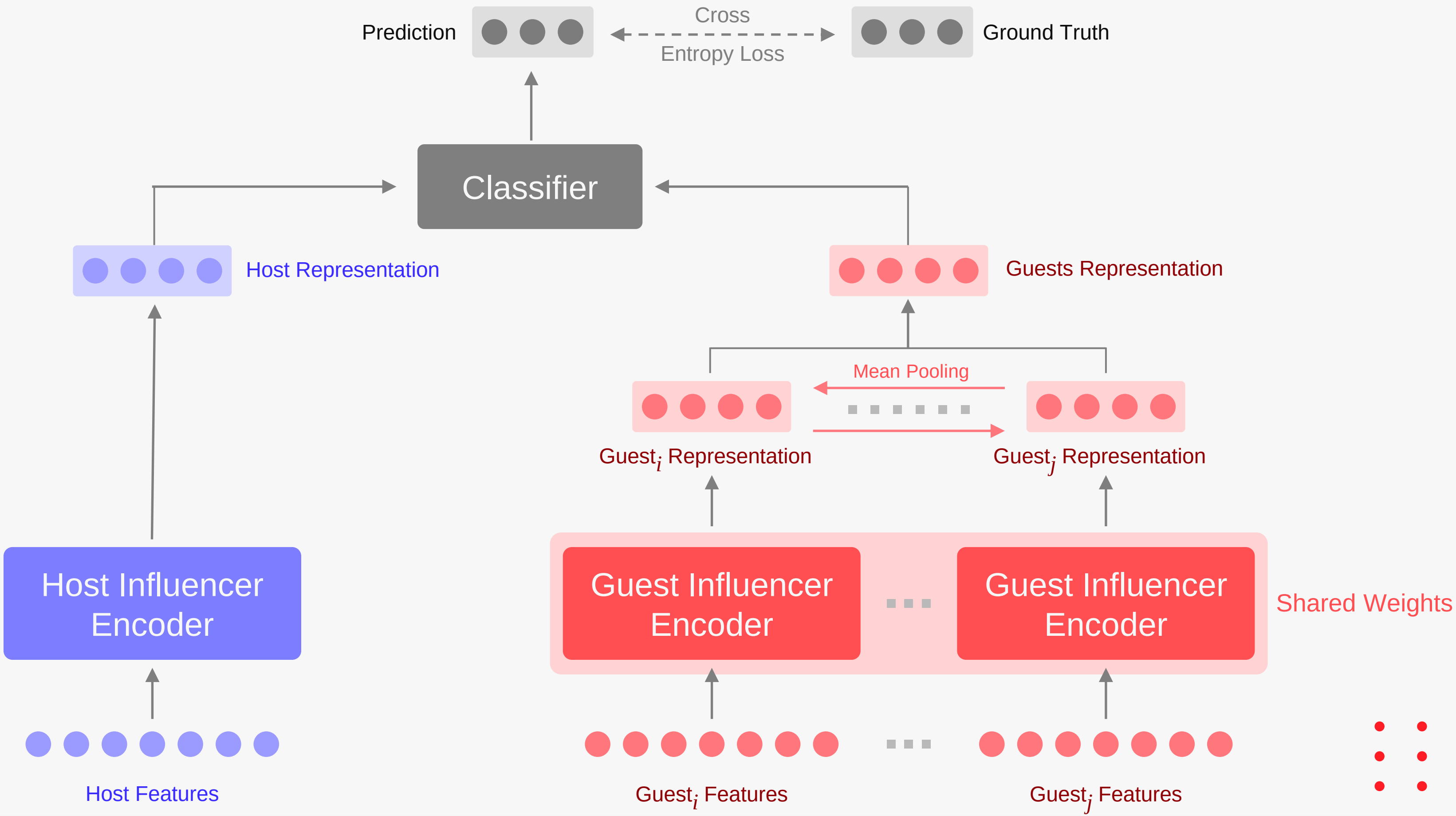
Host Channel

Guest Channel

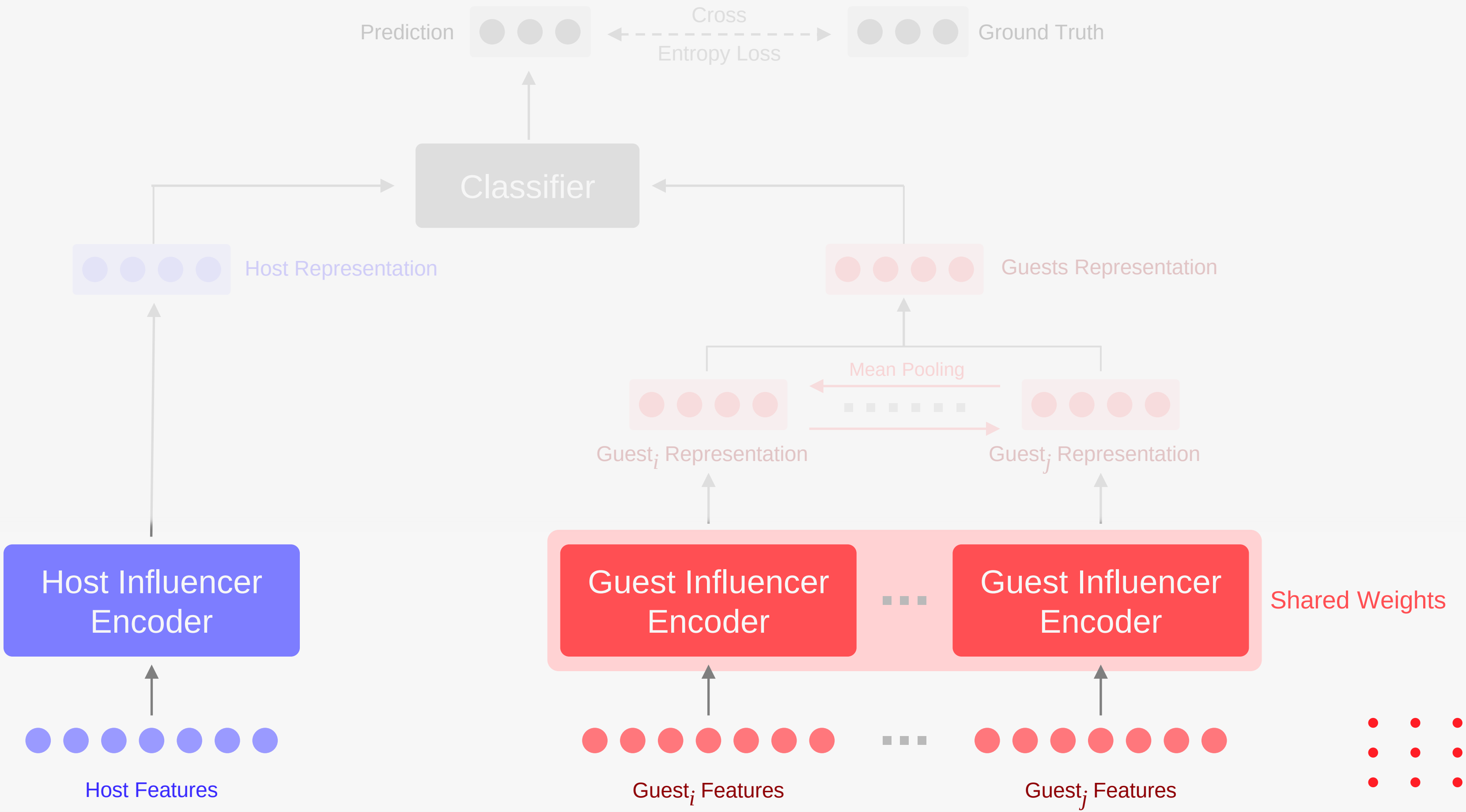


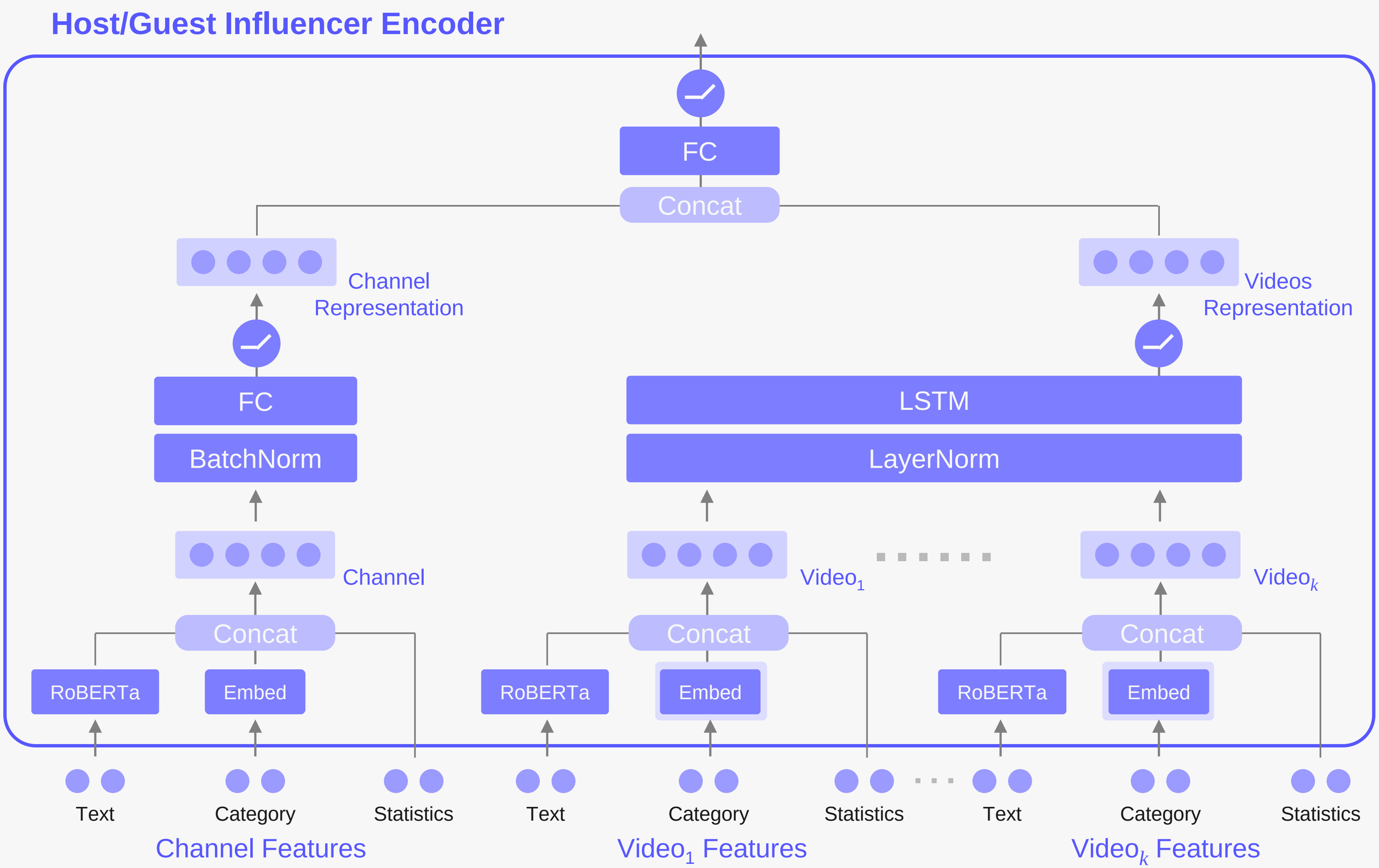
Cannibalization Identification with Influencer Encoder (CIIE)

03 – Model Architecture: CIIE



03 – Model Architecture: CIIE



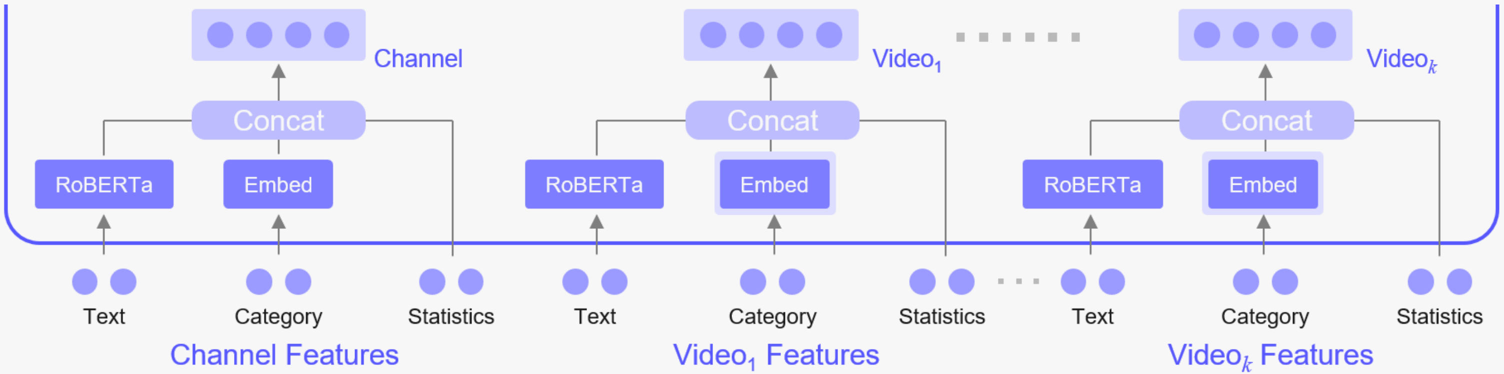

Host/Guest Influencer Encoder
FC
Concat
Channel Representation
Videos Representation
FC
BatchNorm
LSTM
LayerNorm
Channel
Video$_1$
Video$_k$
Concat
Concat
Concat
RoBERTa
Embed
RoBERTa
Embed
RoBERTa
Embed
Text
Category
Statistics
Text
Category
Statistics
Text
Category
Statistics
Channel Features
Video$_1$ Features
Video$_k$ Features

03 – Model Architecture

- Influencer Encoder

The influencer encoder aims to summarize all information about the influencer

- The structure of the influencer encoders for hosts and guests is identical
- They process the same types of inputs in similar ways
  - Text features are concatenated and encoded by Chinese RoBERTa
  - Categorical features are encoded with a learnable embedding layer
  - Statistical features are logarithmized

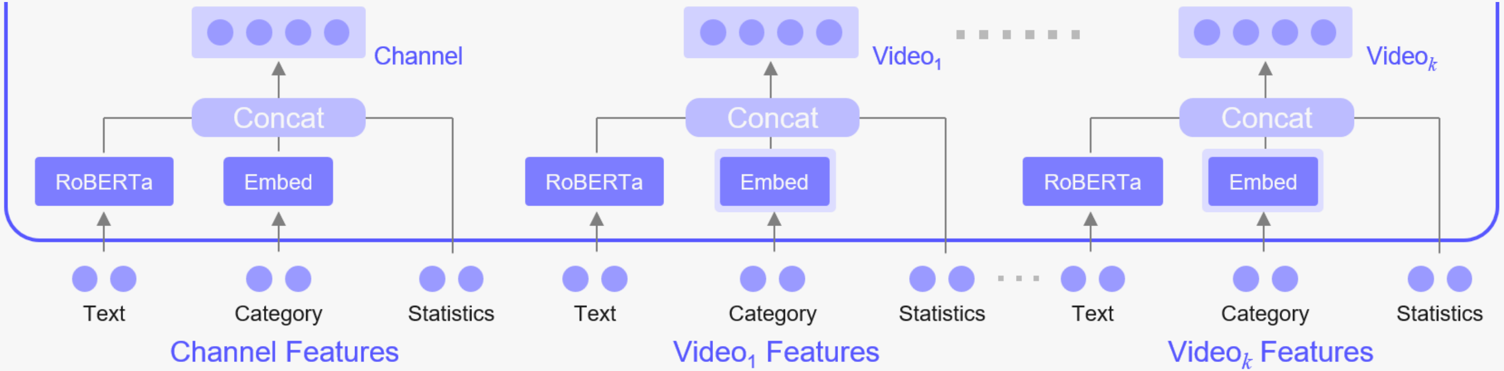


03 – Model Architecture

- Influencer Encoder

The category features of a channel and of a video are different in nature.

- The channel's category feature is multi-valued.
  - Each channel can have a variable number of topic categories. Therefore, to obtain a fixed-sized embedding across all channels, we take the mean of the embeddings of all topic categories to which a channel belongs.
- The video's category feature is single-valued.
  - Therefore, we simply embed each video category into a vector.

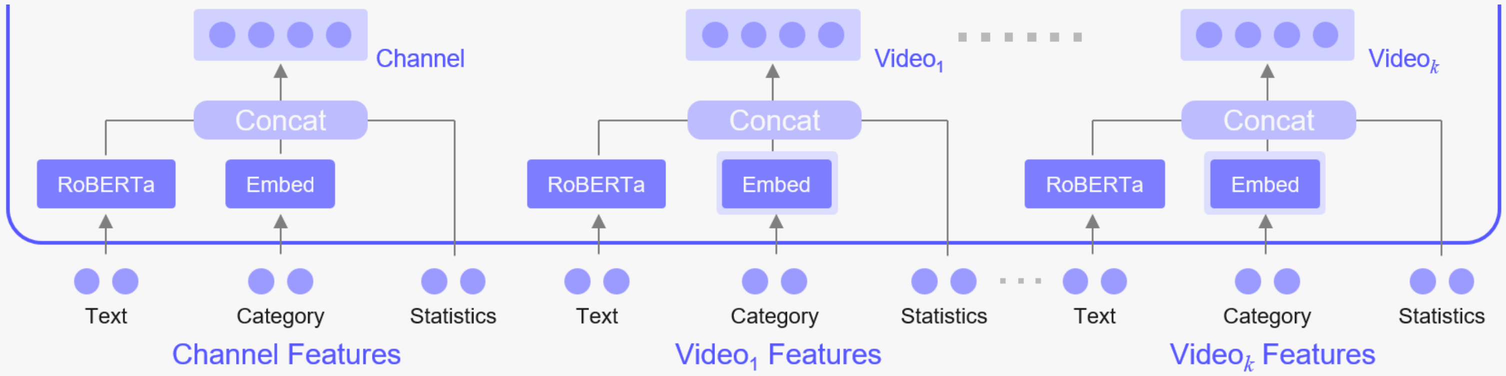


03 – Model Architecture

- Influencer Encoder

It is noteworthy that image features are not considered for this task.

- Images are generally encoded into a high-dimensional space.
- We believe adding such high-dimensional vectors will make the overall vector space too sparse, and the model may fail to strike a balance between all types of features
- In addition, it would make the model too complex by adding too many parameters, slowing down the training process and potentially leading to overfitting.

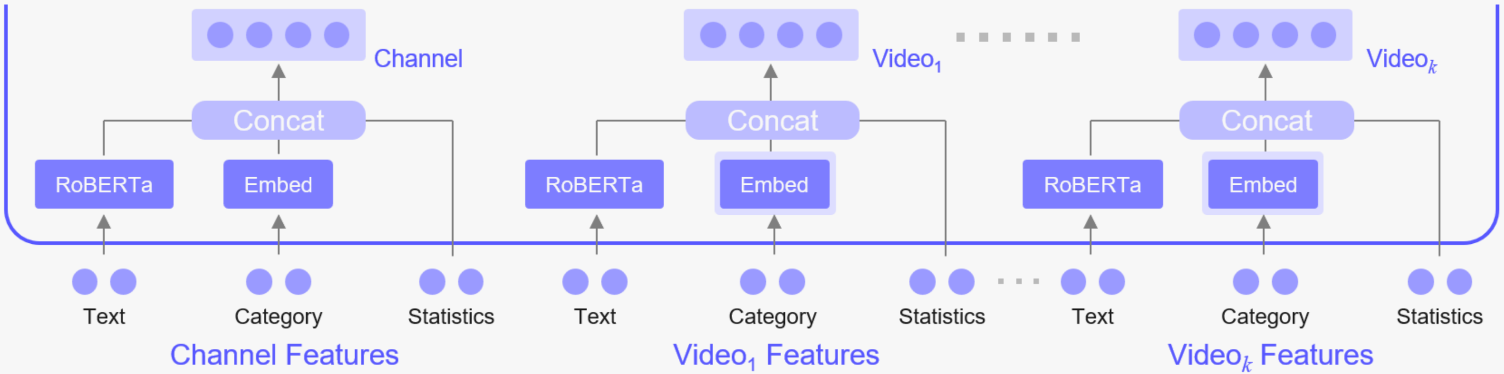


03 – Model Architecture

- Influencer Encoder

After the preprocessing of raw inputs from different channels and videos, each of them has its own numerical representation.

- Therefore, for each influencer, we obtain a channel representation derived from its channel features.
- Additionally, we obtain k video representations that respectively stand for the past k videos prior to a given featured video.

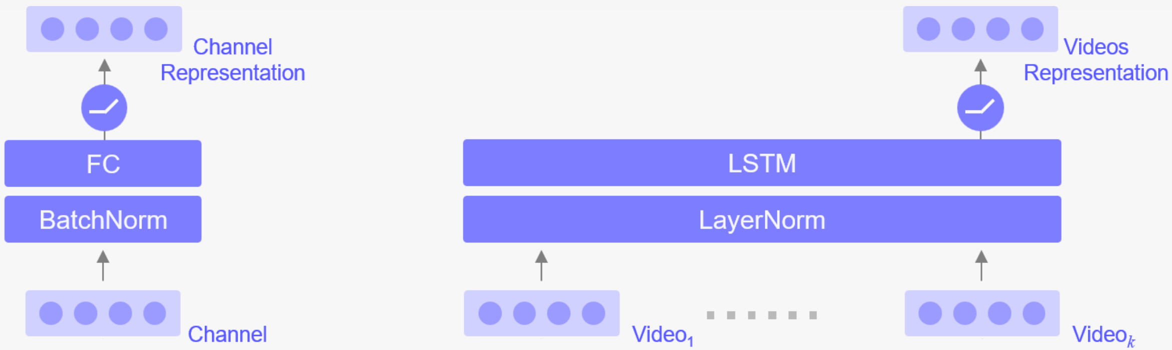


03 – Model Architecture

- Influencer Encoder

The influencer encoder aims to summarize all information about the influencer

- **Channel features** are passed through the below layers:
  - BatchNorm: This normalization layer prevents gradient explosion
  - FC: This is a fully-collected layer that learns the interactions among the multi-modal inputs to generate a channel representation
  - ReLU: An activation function to add nonlinearity to the model

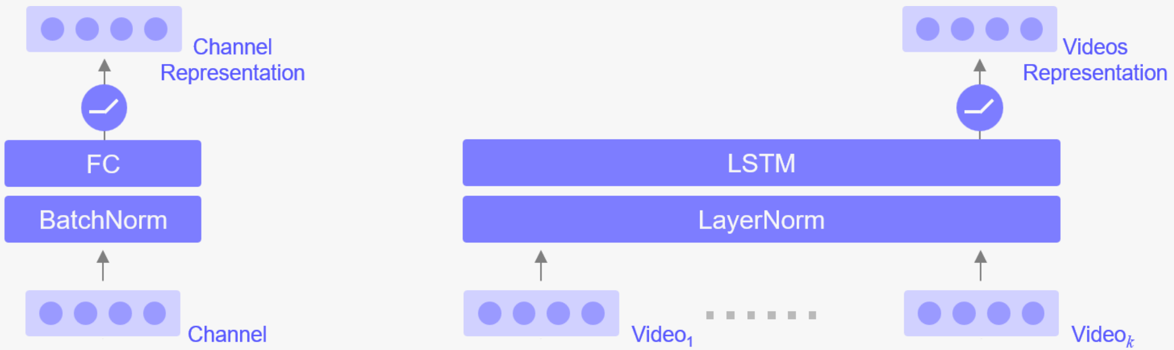


03 – Model Architecture

- Influencer Encoder

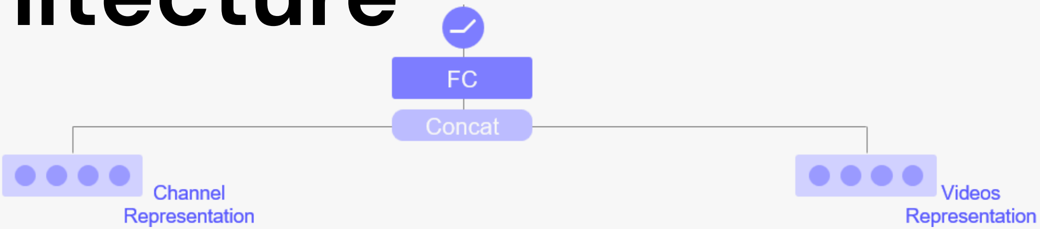
The influencer encoder aims to summarize all information about the influencer

- **Video features** are viewed as a sequence and passed through the below layers:
  - LayerNorm: This normalization layer stabilizes sequential data and prevents gradient explosion
  - LSTM: This layer learns the sequential information along the inputs to generate a video representation, which is the last output hidden state of the layer
  - ReLU: An activation function to add nonlinearity to the model



03 – Model Architecture

- Influencer Encoder

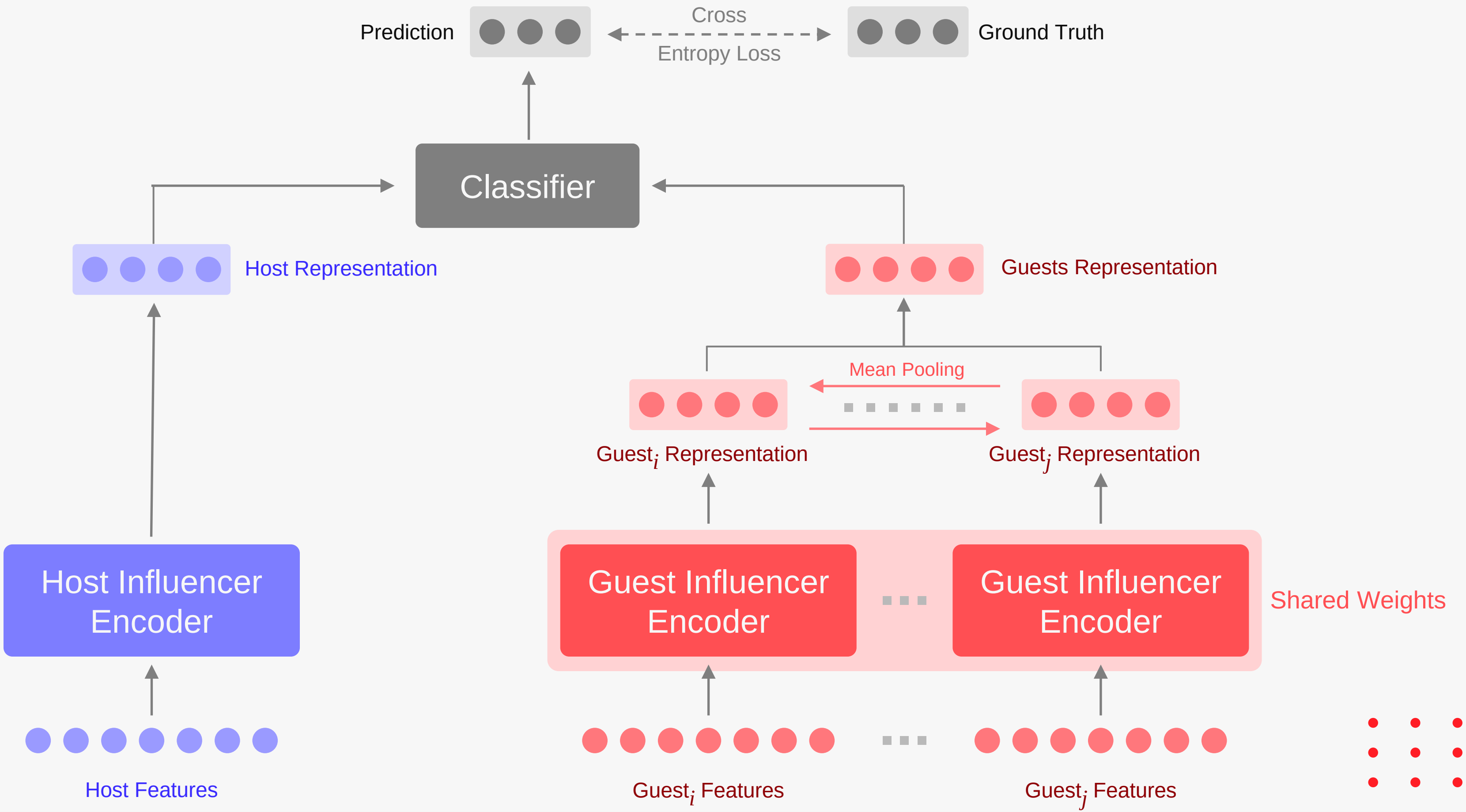


By now, we will obtain two vectors.

- The channel representation of a given influencer
  - This vector is the same for any featured videos
  - This summarizes the general profile of the influencer
- The video representation of a given influencer prior to a specific featured video
  - This vector will be different given different featured videos
  - This captures the current state of the influencer before a collaboration with others

These two vectors are passed through a fully-collected layer (and a ReLU function) to summarize all of the information about a given influencer.

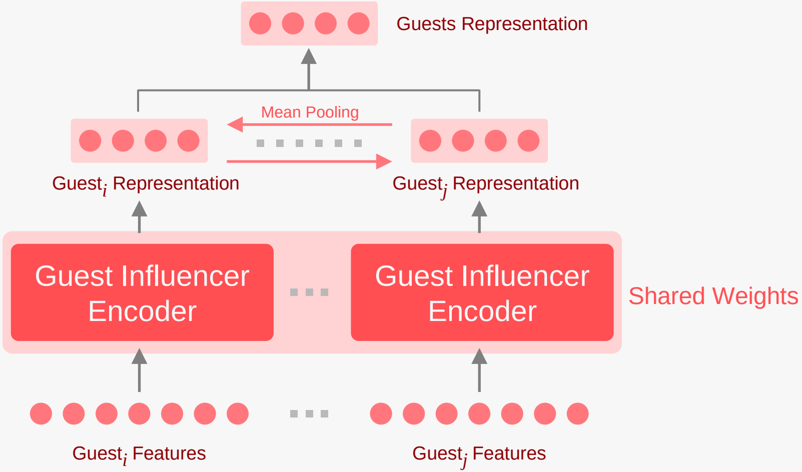
03 – Model Architecture: CIIE



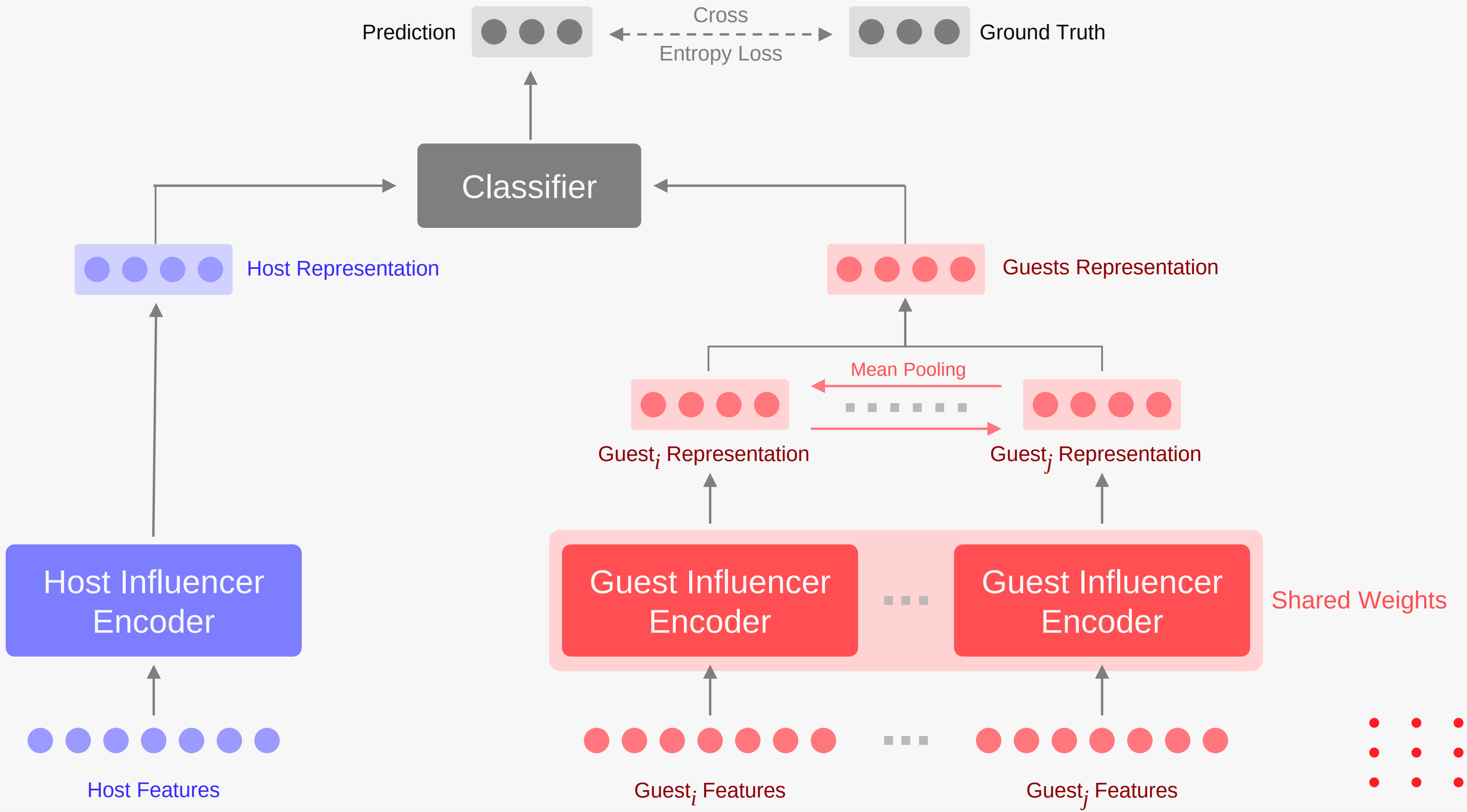
03 – Model Architecture

A mean pooling layer is adopted to generate an overall guest representation

- The guest influencer encoders produces a variable number of guest representations
- Each guest$_i$ is encoded as a guest$_i$ representation, where i = 1 ~ 5
- Their representations are passed through a mean pooling layer to arrive at a general guest representation for a specific featured video k



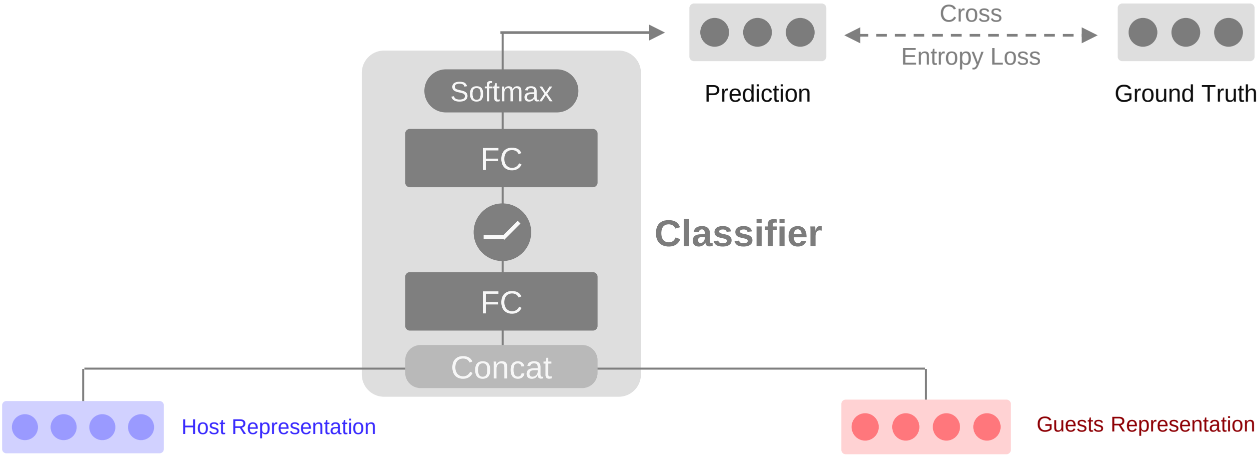
03 – Model Architecture: CIIE



03 – Model Architecture

A simple classifier is adopted to generate the probability distribution for each class

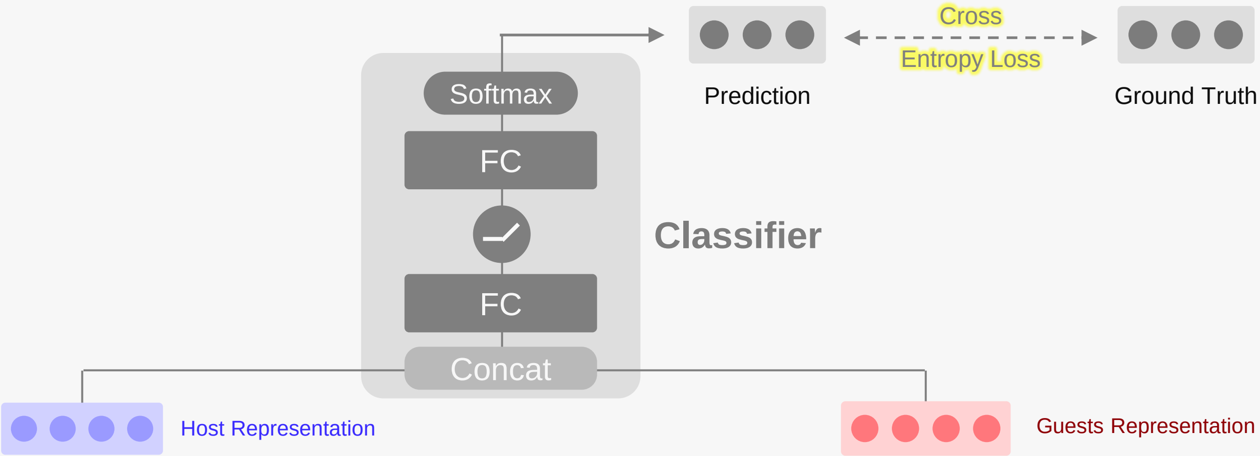
- The host representation and the overall guest representation are concatenated
- They are then passed through two fully-connected layers (and a ReLU function) to learn the relationships between the host and the guests
- Finally, the softmax function generates the probabilities for each class given the inputs



03 – Model Architecture

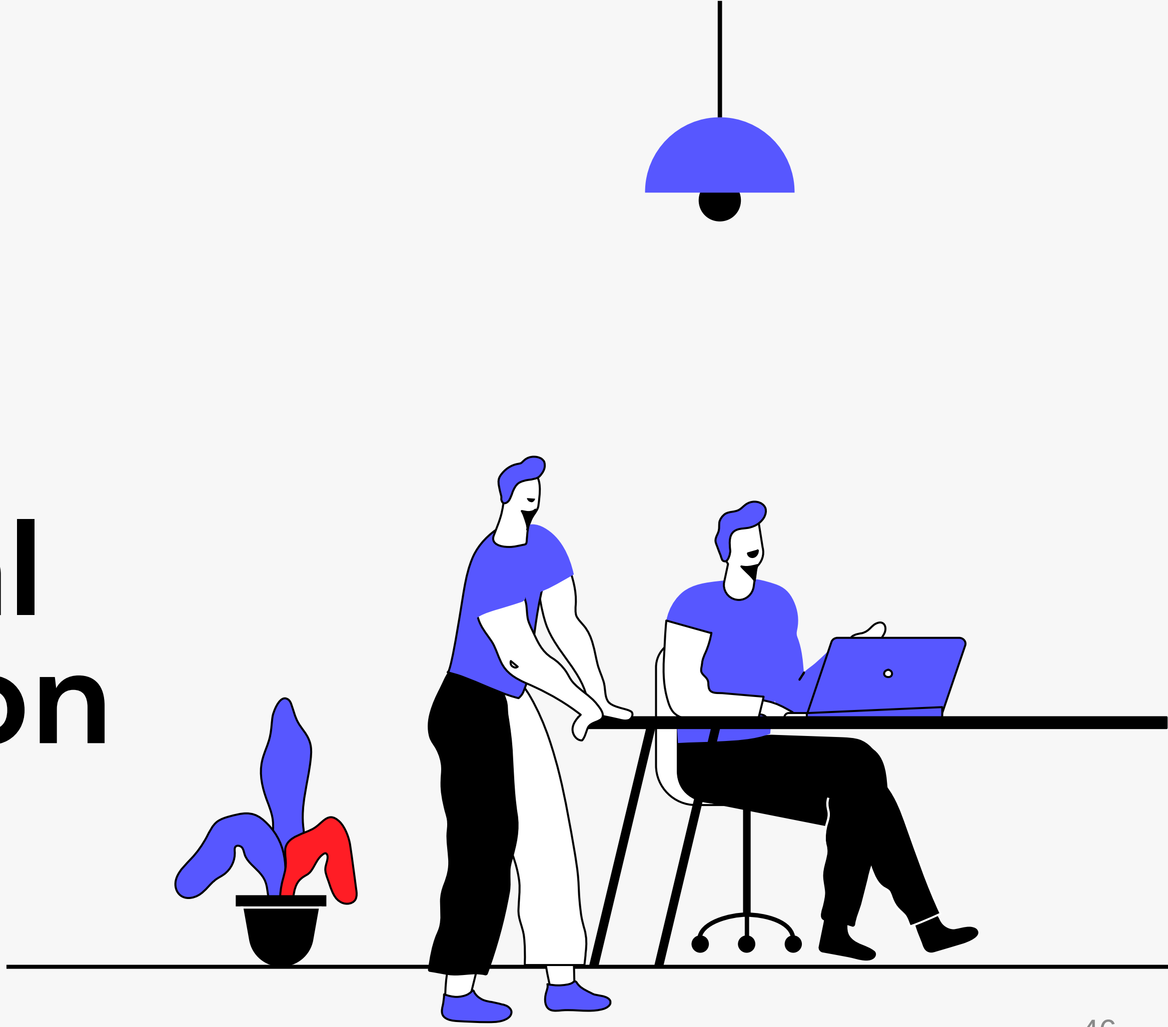
We use class weights to tackle the severe class imbalance problem

- The weight for a given class is the reciprocal of its proportion in the training data
- We assign higher class weights to minority classes, namely, the cannibalized and boosted class, and lower class weights to the majority class, namely, unaffected.
- A cross-entropy loss is adopted for our model



04

Empirical Evaluation



04 – Dataset

Data Collection

Featured Video Identification

Label Construction

Featured Video Filtering

Data Preparation

04 – Dataset

- Data Collection

To investigate the cannibalization prediction problem, we collect channel and video data from 166 influencers in Taiwan using the YouTube API

- These influencers are also known as YouTubers
- By definition, these exclude non-influencer channels, such as singers, musicians, brands, movies, cartoons, and media (news, TV, and radio stations)

The data collection process is conducted in three phases

- We first included the top 50 Taiwan YouTubers listed by Wikipedia (2022)
- Then, we extracted a subset of the most frequently featured guests to these top YouTubers (according to their videos' titles), and add them to our list
- Finally, we repeat the same process to include a third batch of YouTubers
- Note that the data collected might note be the data seen now, as the numbers like video views and subscriber count can change over time

04 – Dataset

- Data Collection

Eventually, we collected a dataset with the below summary statistics:

	Min	Max	Avg	Std
Number of Subscribers	11,300	5,710,000	940,570	899,158
Total Video Views	109,271	2,328,844,865	268,593,094	372,036,752
Average Views Per Video	0.83	17,766.59	2,049.08	2,838.24
Average Featured Videos*	0.00	874.00	90.88	126.38

松松和二毛	葉式特工 Yes Ranger	這群人 TGOP	Pan Piano	阿神	阿滴英文	蔡阿嘎	Joeman	Ru's Piano Ru味春捲	木曜4超玩
571萬	458萬	356萬	347萬	305萬	273萬	253萬	250萬	243萬	233萬

*The identification of featured videos will be detailed later

04 – Dataset

- Data Collection

The dataset is organized on the video level, including channel features and video features. Both of them have four types of information, including text, category, statistics, and images.

Channel features

- Text features: channel title, channel description, channel keywords
- Category features: channel topic categories
- Statistical features: view count, subscriber count, video count, published date
- Image features: channel thumbnail, channel banner

Video features

- Text features: video title, video description, video tags
- Category features: video category
- Statistical features: duration, like count, view count, comment count
- Image features: video thumbnail

04 – Dataset

- Featured Video Identification

We identify a featured video (and its guests) according to the following standards:

- the video title must contain "feat", "ft", or "@"
- the video title must contain at least one name of a YouTuber other than the host, namely, a guest channel
- the guest channel(s) identified in the video title must also be one of the 166 YouTubers we collected, which excludes non-influencer channels entirely

It is worthy to note that the below information is used to identify the presence of a guest YouTuber in a featured video.

- A YouTuber might go by many names and nicknames. Therefore, we manually researched and compiled a list consisting of each YouTuber's different names.
- Each YouTuber also has a username handle provided by YouTube, which is a unique and short channel string identifier.

04 – Dataset

- Label Construction

For each featured video, we labeled it as cannibalized, boosted, or unaffected according to the following process:

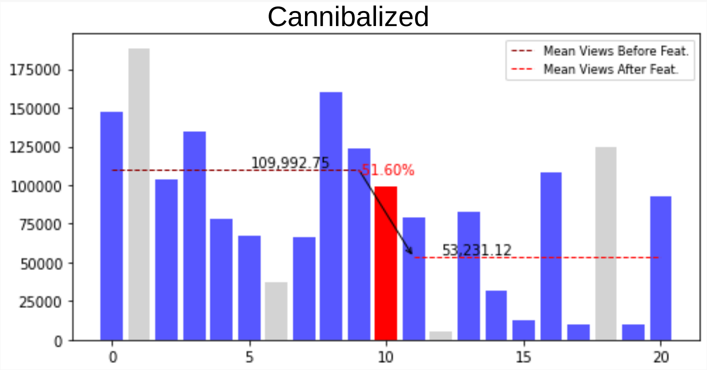
- We used a sliding window of size (k + 1 + k) to scan through videos of each YouTuber
- Whenever a featured video is at the center of the sliding window, we want to compare the average view of its previous k videos and that of its next k videos
- However, we first conduct a simple outlier removal for the calculation of the averages. We remove videos with highest and lowest views for its previous k videos and its next k videos. In total, 4 videos are removed within the same window.
  - This ensures that a label of any featured video is not given based on extreme values.
- Finally, if the average view is observed to drop or rise over θ % after a featured video, then it is labeled as "cannibalized" or "boosted." Otherwise, the video is labeled as "unaffected".

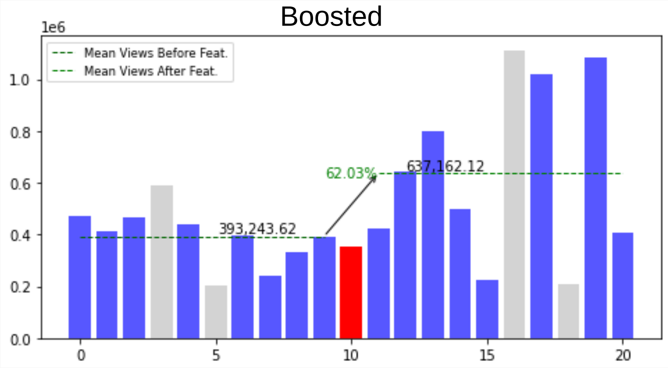
04 – Dataset

- Label Construction

Examples of labeled featured videos:

- The height of the bars indicates the views for each video
- The bar in red (at the tenth position) stands for a featured video
- The bars in grey are videos with min or max views, which are removed when calculating the average views; those in blue are videos used to calculate the averages



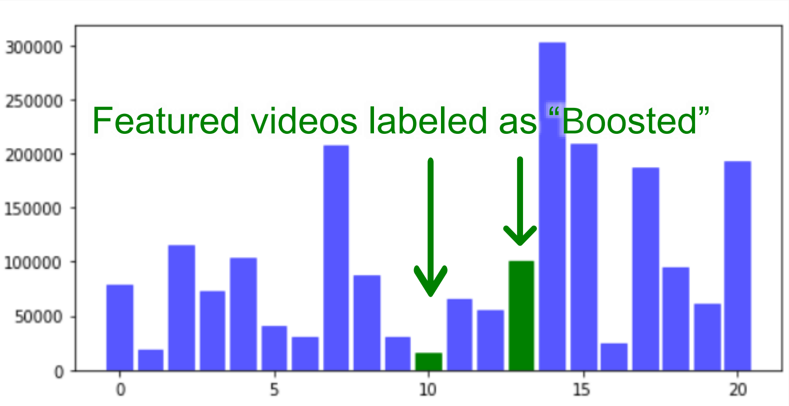


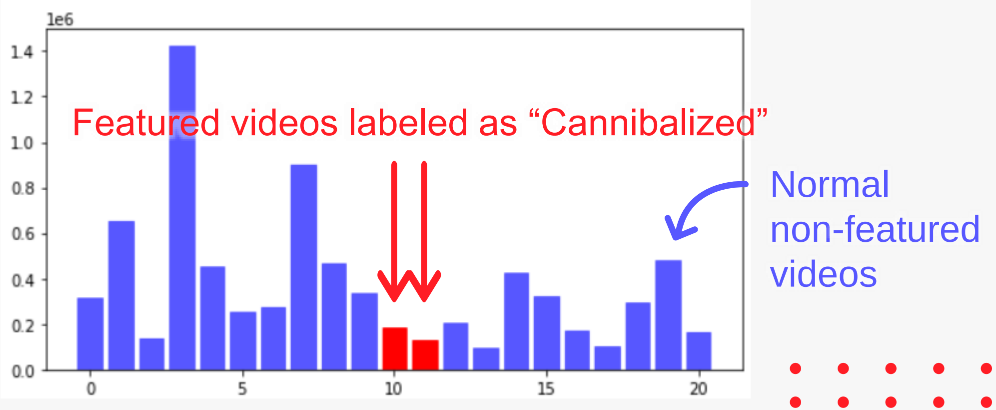
04 – Dataset

- Featured Video Filtering Process

We filter out featured videos that are too close.

- This is because we cannot tell which feature videos contribute to a certain significant rise or drop in average views if two or more featured videos are within the same window
- In such cases, we remove all featured videos in that same window, including the one at the center and its neighboring featured videos, unless they are all “unaffected” videos





04 – Dataset

- Featured Video Filtering Process

Finally, we filter out featured videos that have more than 5 guests:

- This is because featured videos with more than 5 guests are rare and mostly are unaffected videos, which is of little interest to our study
- In addition, to account for videos with a large number of guests, a lot of zero-padding is needed, which will inject too much noise into the model and spike up the number of parameters
- This excludes 180 videos, which is about 3.2% of the total

	Number of labels		
#guests	boosted	cannibalized	unaffected
1	210	111	3,131
2	65	40	941
3	23	18	494
4	21	7	261
5	11	5	109
6	4	1	78
7	1	2	43
8	5	0	31
9	1	0	3
10	1	0	4
11	0	0	1
12	0	1	2
14	1	0	1

04 – Dataset

- Featured Video Filtering Process

In the end, we obtained a set of 5,447 featured videos

- We set k = 10 and θ % = 40%, and are left with 146 YouTubers (who have at least one featured video that are not excluded)

Channel Count	Avg #Subscribers	Avg Total Views	Avg Views per Video	Avg #FeatVideos*
146	851,357.53	245,371,565.84	298,434.00	38.22

- The distribution of the labels are as shown:
  - Class imbalance is conspicuous
  - “Cannibalized”, the main focus of our study, accounts for 3.32% of the featured videos

	Count	Percentage
Unaffected	4,936	90.62%
Boosted	330	6.06%
Cannibalized	181	3.32%

* The average number of featured videos only accounts for those who are not filtered out

04 – Evaluation Procedure

- Experimental Setups

We use stratified 5-fold cross validation to evaluate our model

- A test set of size 897 is first separated for final evaluation
- The rest of 4,550 data is split into stratified 5 folds
  - Training set size = 3,640
  - Validation set size = 910
- The proportion of each class remains the same for training, validation, and testing set

We use precision, recall, and F1 scores as our key metrics for evaluation

- We particularly want to maximize the precision and recall scores on minority classes
- Moreover, we believe the performance on the “cannibalized” class is even more important that “boosted”

04 – Model Configuration

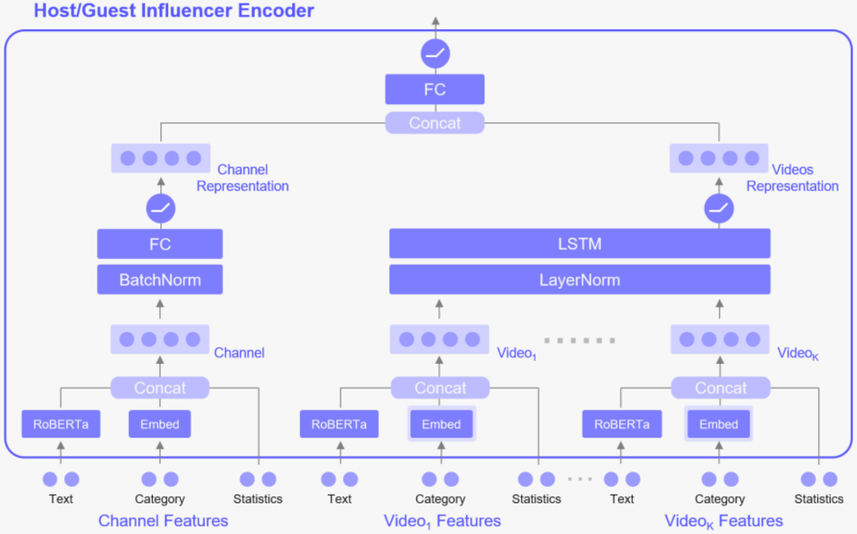
The hyperparameters of our model are as follows.

- batch size = 512
- learning rate = 1e-5
- number of epochs = 2000
- early stopping = 200
- optimizer = Adam
- random seed = 42

04 – Model Configuration

The hidden dimensions of our model are as follows.

- embedding size (of categorical features) = 10
- hidden dim for channel representation = 256
- hidden dim for video representation = 256
- hidden dim for influencer representation = 128
- hidden dim before output layer = 64
- output dim = 3



04 – Evaluation Procedure

- Benchmarks

We evaluate our model against the below benchmarks:

- Prior Probabilistic Model (PPM)
  - The idea is that some guests might have a higher chance of cannibalization or boosting
  - Therefore, we can calculate the prior probability of each class when collaborating with a certain guest influencer
  - The class with the highest prior probability will be the prediction to a featured video whenever he or she is a guest in that video (considering a single-guest case)
- Constrained Prior Probabilistic Model (CPPM)
  - Restrict the proportion of the minority classes to a pre-determined level α
- Random Guess Model (RGM)
  - Randomly assign labels according to a pre-determined class distribution

04 – Evaluation Procedure

- Benchmarks: Prior Probabilistic model (PPM)

The Prior Probabilistic Model (PPM) is trained in the following process

- For each channel, calculate the probability of each class when the channel is a guest to another channel (in the training data)
- Normalize the probabilities to Z-scores with respect to each class across all channels
- Assign the class with the highest Z-score to the channel
  - If there is a tie, then we randomly select one of the class to be the final assignment

	Z-scores			
	boosted	cannibalized	unaffected	**prediction**
Guest 1	-0.568167	-0.396693	-0.628325	cannibalized
Guest 2	-0.568167	-0.626123	-0.628325	boosted
Guest 3	-0.363838	-0.626123	-0.671523	boosted
Guest 4	-0.772496	-0.855554	-0.73632	unaffected
Guest 5	-0.159509	-0.396693	-0.282739	boosted
...	...	...	...	...
Guest 142	-0.363838	-0.855554	-0.585126	boosted
Guest 143	-0.363838	-0.626123	-0.239541	unaffected
Guest 144	NaN	NaN	NaN	unaffected
Guest 145	NaN	NaN	NaN	unaffected
Guest 146	NaN	NaN	NaN	unaffected

04 – Evaluation Procedure

- Benchmarks: Prior Probabilistic model (PPM)

The Prior Probabilistic Model (PPM) makes inference through the following process

- Given a featured video, look up the corresponding class assignments to its guests
  - If the channel does not exist or appear as a guest in the training data, then it is assigned to the “unaffected” label
- Take a majority vote on those assignments, and use the final result as the prediction
  - If there is a tie, randomly sample from one of the majority to be the final prediction

	Guest channels	boosted	cannibalized	unaffected	final_prediction
video 1	{Guest 2, Guest 3, Guest 5}	3	-	-	boosted
video 2	{Guest 4}	-	-	1	unaffected
video 3	{Guest 1,Guest 144}	-	1	2	unaffected
video 4	{Guest 5}	1	-	-	boosted
video 5	{Guest 1, Guest 3}	1	1	-	cannibalized
...	...	...	...	...	...
video N-4	{Guest 99}	1	-	-	boosted
video N-3	{Guest 1, Guest 42}	-	1	1	cannibalized
video N-2	{Guest 146}	-	-	1	unaffected
video N-1	{Guest 42}	-	-	1	unaffected
video N	{Guest 10}	-	-	1	unaffected

04 – Evaluation Procedure

- Benchmarks: Constrained Prior Probabilistic model (CPPM)

The Constrained Prior Probabilistic Model is trained in the following process

- Define a minority percentage α
- Run the training process of the Prior Probabilistic model
- For all channels assigned to “cannibalized”, find those whose Z scores in the “cannibalized” label are not in the top α percent, and reassign them to “unaffected”. The same applies to those assigned to “boosted”.
  - This constrains the percentage of “cannibalizing” and “boosting” channels to a small fixed pre-determined proportion
- α is set to 0.1 and 0.05 for evaluation purposes

The inference process is the same as that of the Prior Probabilistic model (PPM)

04 – Evaluation Procedure

- Benchmarks: Random Guess Model (RGM)

The Random Guess Model (RGM) is trained in the following process

- For each channel, randomly assign labels to each channel (in the training data) according to a pre-determined probability distribution of the three classes
  - For example, probability of (cannibalized, boosted, unaffected) = (10%, 10%, 80%)

The inference process is the same as that of the Prior Probabilistic model (PPM)

To calculate the metrics, we run the above training and inference process 1000 times for each fold, and take their averages.

04 – Evaluation Results

	Cannibalized			**Boosted**			**Unaffected**			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
RGM (10%-10%-80%)	0.0862	0.0871	0.0830	0.0902	0.0860	0.0841	0.8232	0.8219	0.8217	0.3332	0.3317	0.3296
RGM (5%-5%-90%)	0.0879	0.0427	0.0536	0.0903	0.0413	0.0528	0.8237	**0.9139**	**0.8661**	0.3340	0.3326	0.3242
PPM	0.0957	0.3929	0.1538	0.1238	**0.4533**	0.1942	**0.8720**	0.3348	0.4828	0.3638	0.3937	0.2769
CPPM (α = 10%)	0.0890	0.1905	0.1209	0.1183	0.3000	0.1695	0.8389	0.5963	0.6968	0.3487	0.3623	0.3291
CPPM (α = 5%)	0.0777	0.1071	0.0893	0.0813	0.1222	0.0974	0.8222	0.7444	0.7811	0.3271	0.3246	0.3226
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	0.4111	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

Our model has better overall performance in terms of precision, recall, and F1-score

- Metrics of our model on the minority classes (cannibalized & boosted) are superior to those of other benchmarks, excepted for the recall on the “boosted” class
- Our model’s recall in “boosted”, however, is not too far from the best one given by PPM, which prefers to predict minority classes, as will be discussed later
- Our result on the macro average of the metrics are also better, but since it takes into account the outcome of the unaffected class, it is not our main focus

04 – Evaluation Results

	Cannibalized			**Boosted**			**Unaffected**			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
RGM (10%-10%-80%)	0.0862	0.0871	0.0830	0.0902	0.0860	0.0841	0.8232	0.8219	0.8217	0.3332	0.3317	0.3296
RGM (5%-5%-90%)	0.0879	0.0427	0.0536	0.0903	0.0413	0.0528	0.8237	**0.9139**	**0.8661**	0.3340	0.3326	0.3242
PPM	0.0957	0.3929	0.1538	0.1238	**0.4533**	0.1942	**0.8720**	0.3348	0.4828	0.3638	0.3937	0.2769
CPPM (α = 10%)	0.0890	0.1905	0.1209	0.1183	0.3000	0.1695	0.8389	0.5963	0.6968	0.3487	0.3623	0.3291
CPPM (α = 5%)	0.0777	0.1071	0.0893	0.0813	0.1222	0.0974	0.8222	0.7444	0.7811	0.3271	0.3246	0.3226
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	0.4111	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

Our model has better performance in the “cannibalized” and “boosted” class in terms of precision, recall, and F1-score

- The precision for minority classes is higher than those of other benchmarks
- The recall for “cannibalized” is significantly higher than any other benchmarks
- This suggests that our model did capture important information that is helpful for detecting cannibalization, as well as boosting effect, for a potential featured video
- This reflects our efforts to address class imbalance has proven to be fruitful

04 – Evaluation Results

	Cannibalized			Boosted			Unaffected			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
RGM (10%-10%-80%)	0.0862	0.0871	0.0830	0.0902	0.0860	0.0841	0.8232	0.8219	0.8217	0.3332	0.3317	0.3296
RGM (5%-5%-90%)	0.0879	0.0427	0.0536	0.0903	0.0413	0.0528	0.8237	**0.9139**	**0.8661**	0.3340	0.3326	0.3242
PPM	0.0957	0.3929	0.1538	0.1238	**0.4533**	0.1942	**0.8720**	0.3348	0.4828	0.3638	0.3937	0.2769
CPPM (α = 10%)	0.0890	0.1905	0.1209	0.1183	0.3000	0.1695	0.8389	0.5963	0.6968	0.3487	0.3623	0.3291
CPPM (α = 5%)	0.0777	0.1071	0.0893	0.0813	0.1222	0.0974	0.8222	0.7444	0.7811	0.3271	0.3246	0.3226
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	0.4111	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

PPM is overall the second best model in terms of overall metrics across all classes

- This suggests that the Z-scores of each classes for each channel does carry useful information for predicting cannibalization effects.
- It outperforms the RGM baseline in almost all metrics, making it a comparable benchmark to evaluate against.
- It is noticeable that the recall of PPM is significantly larger for minority classes and lower for the majority class, which suggests that prefers to predict minority classes

04 – Evaluation Results

	Cannibalized			Boosted			Unaffected			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
RGM (10%-10%-80%)	0.0862	0.0871	0.0830	0.0902	0.0860	0.0841	0.8232	0.8219	0.8217	0.3332	0.3317	0.3296
RGM (5%-5%-90%)	0.0879	0.0427	0.0536	0.0903	0.0413	0.0528	0.8237	**0.9139**	**0.8661**	0.3340	0.3326	0.3242
PPM	0.0957	0.3929	0.1538	0.1238	**0.4533**	0.1942	**0.8720**	0.3348	0.4828	0.3638	0.3937	0.2769
CPPM (α = 10%)	0.0890	0.1905	0.1209	0.1183	0.3000	0.1695	0.8389	0.5963	0.6968	0.3487	0.3623	0.3291
CPPM (α = 5%)	0.0777	0.1071	0.0893	0.0813	0.1222	0.0974	0.8222	0.7444	0.7811	0.3271	0.3246	0.3226
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	0.4111	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

RGM has the highest recall and F1-scores in the majority class

- However, this make sense because we set the probability of sampling the “unaffected” label to be 90%. This makes its recall to be around 90% as well, in this case, 91.39%
- The exceptionally high recall score in turn drives up the F1-score
- As the performance of the majority class is not our research focus, we can safely disregard concerns about its outstanding recall and F1-score

04 – Evaluation Results

	Cannibalized			Boosted			Unaffected			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
RGM (10%-10%-80%)	0.0862	0.0871	0.0830	0.0902	0.0860	0.0841	0.8232	0.8219	0.8217	0.3332	0.3317	0.3296
RGM (5%-5%-90%)	0.0879	0.0427	0.0536	0.0903	0.0413	0.0528	0.8237	**0.9139**	**0.8661**	0.3340	0.3326	0.3242
PPM	0.0957	0.3929	0.1538	0.1238	**0.4533**	0.1942	**0.8720**	0.3348	0.4828	0.3638	0.3937	0.2769
CPPM (α = 10%)	0.0890	0.1905	0.1209	0.1183	0.3000	0.1695	0.8389	0.5963	0.6968	0.3487	0.3623	0.3291
CPPM (α = 5%)	0.0777	0.1071	0.0893	0.0813	0.1222	0.0974	0.8222	0.7444	0.7811	0.3271	0.3246	0.3226
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	0.4111	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

CPPM falls short compared to PPM in every metric

- It makes sense that the recall of the minority classes drops and that of the majority class increases as we set a lower value for α, because we are explicitly predicting less minority labels and more majority labels
- However, the precision drops for all classes, which might be attributed to the fact that the Z-scores of minority classes do not account for their frequency. For example, if a channel is a guest only once and that featured video happened to be “cannibalized”, the corresponding Z-score is high, but is not predictive of future collaborations.

04 – Evaluation Results

	Cannibalized			Boosted			Unaffected			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
RGM (10%-10%-80%)	0.0862	0.0871	0.0830	0.0902	0.0860	0.0841	0.8232	0.8219	0.8217	0.3332	0.3317	0.3296
RGM (5%-5%-90%)	0.0879	0.0427	0.0536	0.0903	0.0413	0.0528	0.8237	**0.9139**	**0.8661**	0.3340	0.3326	0.3242
PPM	0.0957	0.3929	0.1538	0.1238	**0.4533**	0.1942	**0.8720**	0.3348	0.4828	0.3638	0.3937	0.2769
CPPM (α = 10%)	0.0890	0.1905	0.1209	0.1183	0.3000	0.1695	0.8389	0.5963	0.6968	0.3487	0.3623	0.3291
CPPM (α = 5%)	0.0777	0.1071	0.0893	0.0813	0.1222	0.0974	0.8222	0.7444	0.7811	0.3271	0.3246	0.3226
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	0.4111	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

CPPM achieves higher recall than RGM, but with no notable difference in precision, considering only the minority classes

- This means it performs better than RGM (although poorer than PPM as discussed)
- The higher recall indicates CPPM’s capability in capturing more true “cannibalized” and “boosted” labels
- The insignificant difference in precision means that CPPM and RGM are equally good at avoiding false positive predictions.

04 – Evaluation Results

- Ablation Test 1: Influence of Different Inputs on Model Performance

	Cannibalized			**Boosted**			**Unaffected**			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
CIIE w/o Text	0.1351	0.4786	0.2107	0.1338	0.4089	0.2013	0.8638	0.4412	0.5837	0.3776	0.4429	0.3319
CIIE w/o Cats	0.1313	0.4286	0.1981	0.1304	0.3778	0.1915	**0.8714**	**0.4760**	**0.6055**	0.3777	0.4274	0.3317
CIIE w/o Stats	0.1117	0.4524	0.1786	**0.1354**	0.4000	**0.2014**	0.8813	0.4137	0.5608	0.3761	0.4220	0.3136
CIIE	**0.1471**	**0.4833**	**0.2246**	0.1353	**0.4111**	**0.2014**	0.8707	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

Removing any type of inputs leads to a decline in overall model performance

- For the cannibalized class, statistics features has the most impact in both precision and recall scores, while the text features are the least influential
- For the boosted class, category features has the most impact in both precision and recall scores, while statistics features are the least influential
- The metrics for the majority class, though not the best, is of little difference from other scenarios. Additionally, our research focuses on minority classes; therefore, it should raise no concern.

04 – Evaluation Results

- Ablation Test 2

	Cannibalized			**Boosted**			**Unaffected**			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
CIIE w/ Image*	0.1159	0.4095	0.1767	0.1186	0.2956	0.1687	0.8611	**0.4875**	**0.6154**	0.3652	0.3975	0.3203
CIIE	**0.1471**	**0.4833**	**0.2246**	**0.1353**	**0.4111**	**0.2014**	**0.8707**	0.4647	0.6000	**0.3844**	**0.4531**	**0.3420**

Adding image inputs, including thumbnails and banners, are harmful to the overall performance of the model

- There is a notable decline in all metrics of the minority classes
  - As discussed, we believe the addition of high-dimensional image vectors makes the vector space too sparse and model struggle to balance all types of features.
  - Moreover, the increased complexity from adding excessive parameters, besides significantly slowing down the training process, could lead to overfitting
- Removing image inputs only slightly improves the recall and F1-score of the majority class, which is not the research focus.

*The image inputs are encoded with ResNet into 1000-dimensional vectors

04 – Evaluation Result

- Effect of Class Imbalance Methods on Classification Effectiveness

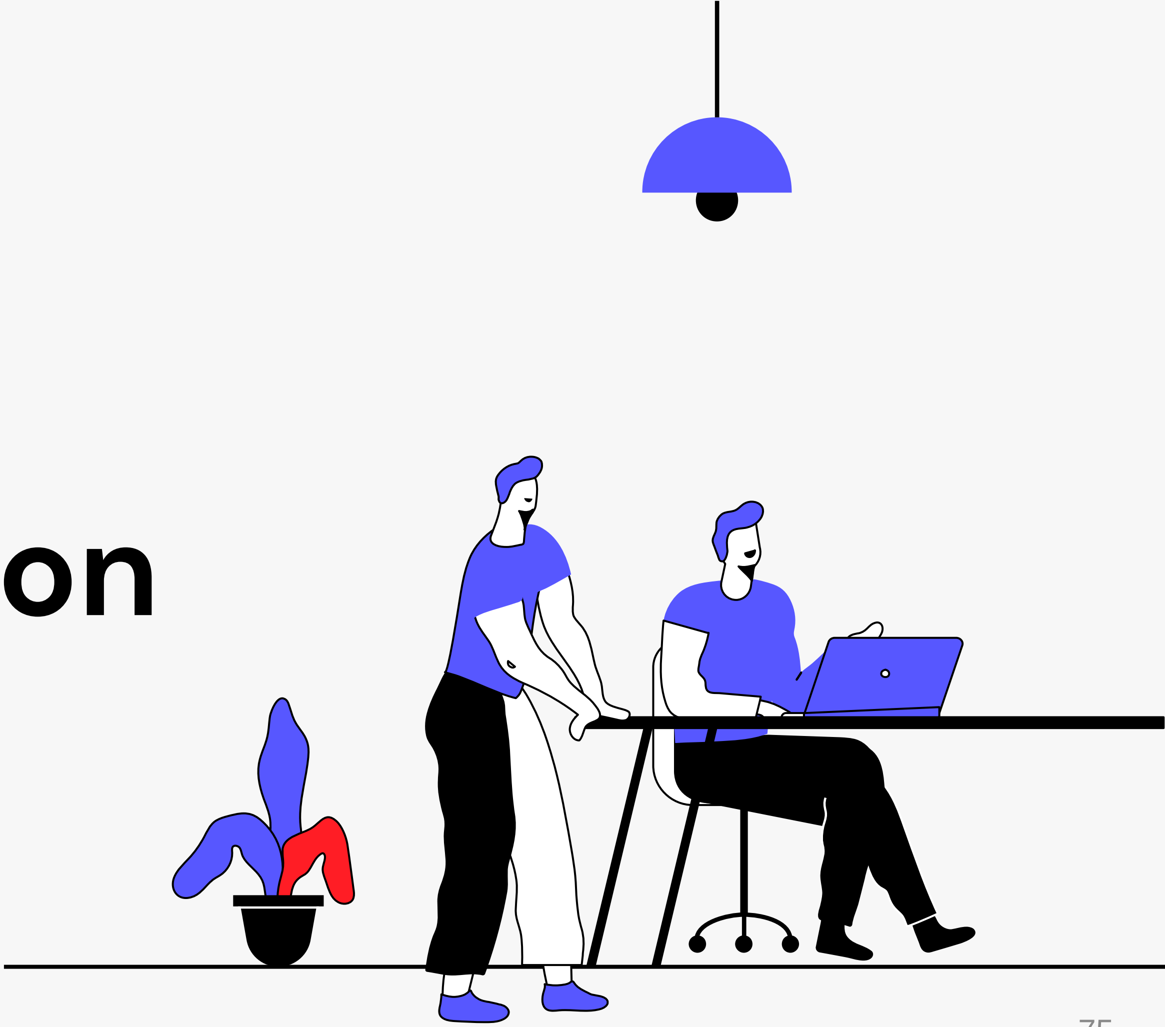
	Cannibalized			**Boosted**			**Unaffected**			macro avg		
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score
No adjustment	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8242	1.0000	**0.9037**	0.2747	0.3333	0.3012
ADASYN	**0.1664**	0.0786	0.1060	0.1439	0.0733	0.0965	0.8312	**0.9172**	0.8720	0.3805	0.3564	0.3582
SMOTE	0.1628	0.0881	0.1101	**0.1537**	0.0756	0.0996	0.8295	0.9130	0.8691	0.3820	0.3589	**0.3596**
BorderlineSMOTE	0.1317	0.0714	0.0912	0.1229	0.0667	0.0859	0.8274	0.9044	0.8642	0.3606	0.3475	0.3471
Class Weights	0.1491	**0.4405**	**0.2215**	0.1457	**0.4733**	**0.2221**	**0.8755**	0.4775	0.6151	**0.3901**	**0.4638**	0.3529

Class weights prove to be the best; using other class imbalance methods leads to a decline in overall model performance

- First of all, without any measures taken to handle class imbalance, the model simply classifies all samples to the majority class
- ADASYN and SMOTE produce slightly better precision for the cannibalized and boosted labels, respectively, but at the huge expense of remarkably low recall in minority classes
- BorderlineSMOTE worsens the model's performance across all metrics

05

Conclusion



05 – Contribution

- Presents a novel cannibalization definition and predictive DNN model for featured videos by influencers

This research makes contributions in the following aspects:

- We defined a novel research task, i.e., cannibalization effect prediction in the context of featured videos by social media influencers, and found evidence that cannibalization indeed occurred in the featured videos investigated.
- We proposed a DNN predictive model to resolve such a problem, with influencer encoders capturing essential information about the host and guest influencers and their content. This model is evaluated against and outperforms all benchmark methods, which enables us to gauge its effectiveness in various aspects.

Overall, this work presents a comprehensive analysis of cannibalization among social media influencers and provides valuable insights into the development of an effective predictive model.

05 – Future Research Directions

- Our work also sheds light on several aspects that can be improved in future research

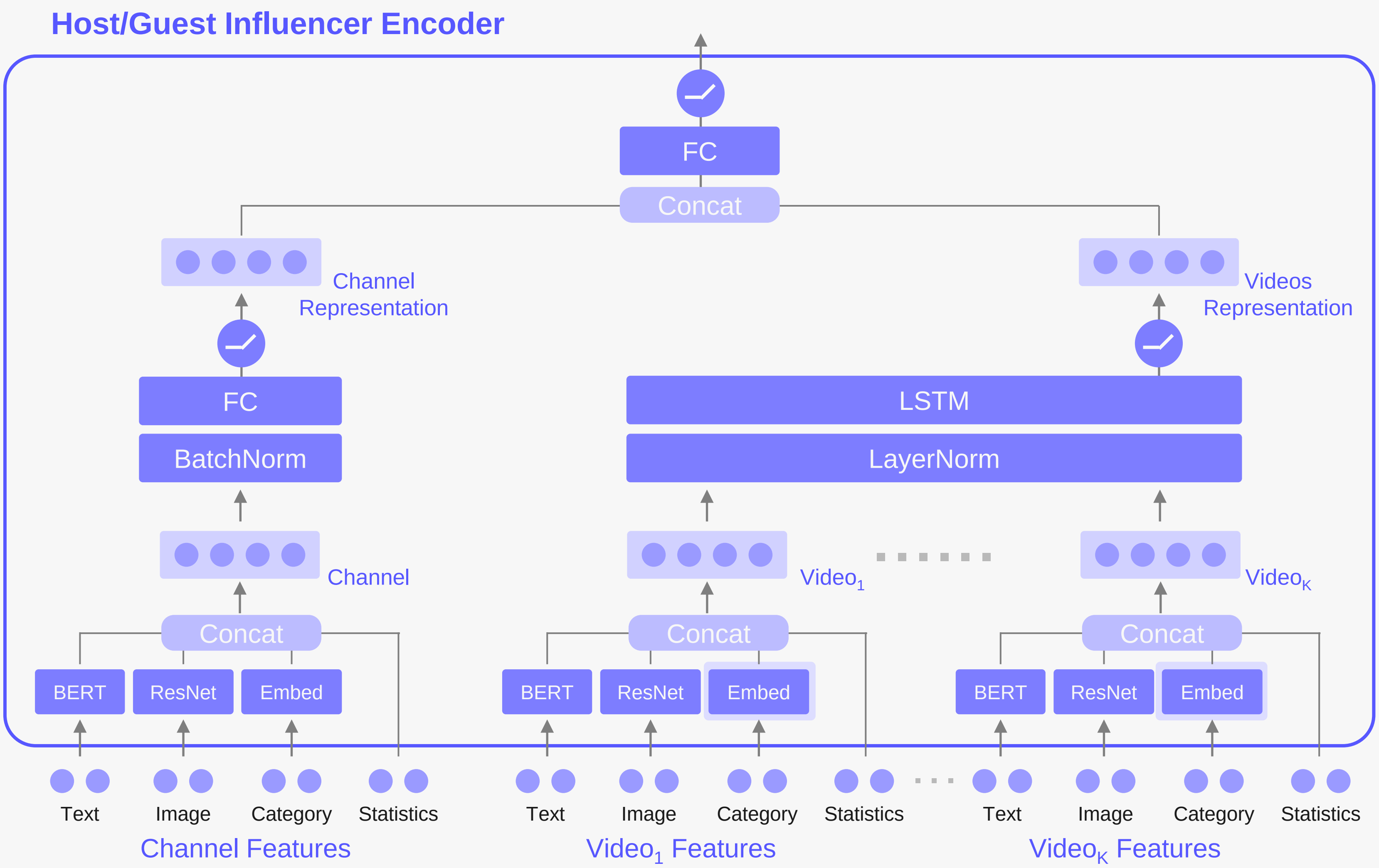
Future work

- Collecting a larger dataset would enhance comprehensiveness, as the current number of remaining featured videos after filtering is 5,447.
- The scope of the data is restricted to Taiwanese YouTubers, thereby limiting its generalizability to influencers on other platforms or in different countries. Collecting additional datasets from different platforms or incorporating YouTubers from different countries represents an interesting research direction.
- The operational definition of cannibalization in our context uses only video views. However, incorporating user behaviors such as likes and comments can better gauge viewers' preferences and refine the definition.
- Content of the video itself may also be important, but is currently disregarded in this preliminary work because the model complexity would be too high given the limited data at hand.

Thanks!

06

Appendix


Host/Guest Influencer Encoder
FC
Concat
Channel Representation
Videos Representation
FC
BatchNorm
LSTM
LayerNorm
Channel
Video$_1$
Video$_K$
Concat
Concat
Concat
BERT
ResNet
Embed
BERT
ResNet
Embed
BERT
ResNet
Embed
Text
Image
Category
Statistics
Text
Image
Category
Statistics
Text
Image
Category
Statistics
Channel Features
Video$_1$ Features
Video$_K$ Features