Viral Video Style: A Closer Look at Viral Videos on YouTube

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Outline

- Introduction
- CMU Viral Video Dataset
- Statistical Characteristics
- Peak Day Prediction
- Conclusions

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What is a viral video?

- A viral video is a video that becomes popular through the process of (most often) Internet **sharing** through **social media**.

Gangnam Style

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- A viral video is a video that becomes popular through the process of (most often) Internet sharing through social media.

Charlie bit my finger

Gangnam Style

Missing pilot MH370

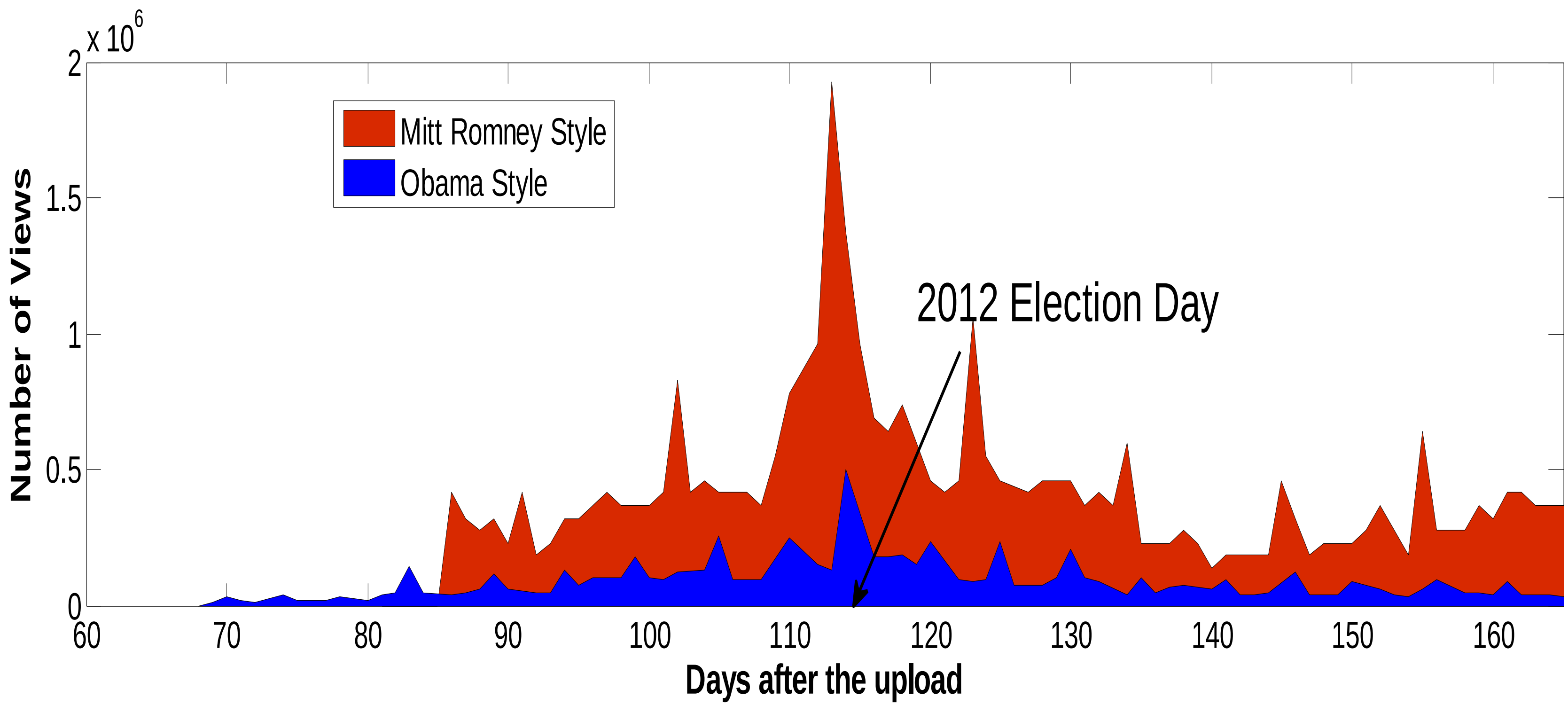
Social Validity

- Viral videos have been having a **profound impact** on many aspects of society.
- Politics:
  – Pro-Obama video "Yes we can" went viral (10 million views) in 2008 US presidential election [Broxton 2013].

Social Validity

- Viral videos have been having a profound impact on many aspects of society.
- Politics:
  - Pro-Obama video “Yes we can” went viral (10 million views) in 2008 US presidential election [Broxton 2013].
  - We found that Obama Style and Mitt Romney Style went viral (30 million views in the month of Election Day), and **peaked on Election Day**.

Social Validity



Social Validity cont.

- Viral videos have been having a profound impact on many aspects of society.
- **Financial marketing**:
  - Old Spice’s campaign went viral and improved the brand’s popularity among young customers[West et al 2011].

Social Validity cont.

- Viral videos have been having a profound impact on many aspects of society.
- Financial marketing:
  - Old Spice's campaign went viral and improved the brand's popularity among young customers[West et al 2011].
  - Psy's commercial deals has amounted to 4.6 million dollars from Gangnam Style.

Motivation

- Existing studies are conducted on:
  - Small set (tens of videos) → biased observations?
  - Large-scale Google set → confidential!
- A relatively large and public dataset on viral videos would be conducive.
- Solution: CMU Viral Video Dataset.

Beware the content are hilarious!

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CMU Viral Video Dataset

- By far the **largest** public viral video dataset. Time's list was the largest dataset (50 videos).
- Videos are **manually selected by experts**
  - Editors from Time Magazine, YouTube and the viral video review episodes.
- Statistics: 446 viral videos, 294 quality 19,260 background videos.

10+ million subscribers!

CMU Viral Video Dataset Cont.

- For a video, it includes:
  - Thumbnail
  - Video and user metadata

CMU Viral Video Dataset Cont.

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  - Thumbnail
  - Video and user metadata
  - Insight data: historical views, likes, dislikes, etc.

Date	Day	View
12/18/2012	0	1296022
12/19/2012	1	15552276
12/20/2012	2	8025373
12/21/2012	3	3987763
12/22/2012	4	2990822
12/23/2012	5	2392658
12/24/2012	6	2093575

CMU Viral Video Dataset Cont.

- For a video, it includes:
  - Thumbnail
  - Video and user metadata
  - Insight data: historical views, likes, dislikes, etc.
  - Social data: #Inlinks, daily tweeter mentions (pending)

[Number of In-links]
624000

[#Tweets mentioned]

Date	#Tweets with Video ID
12/18/2012	0
12/18/2012	79
12/19/2012	14
12/20/2012	3
12/21/2012	7

CMU Viral Video Dataset Cont.

(a) ID: rYEDA3JcQqw (b) ID:mBRUkdQa6Is

(c) ID: _OBlgSz8sSM (d) ID: Y13oB-IhE7I

– Near duplicate videos (automatic detection + manual inspection).

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Statistical Characteristics

Table 3: Basic statistics about viral videos.

Statistics	Viral	Quality	Background
View Count Median	3,079,011	55,455,364	7,528
Title length	5.0±0.1	5.4±0.1	7.0±0.1
Duration(s)	138.6±16.0	248±3.9	252±24.6
Average Rate	4.69±0.03	4.75±0.03	4.04±0.08
Rater/View	0.54±.03%	0.38±.01%	0.87 ±.07%
Cor(inlinks, view)	0.54	0.25	0.28
Days-to-peak Median	24	63	30
Lifespan Median	7	166	10

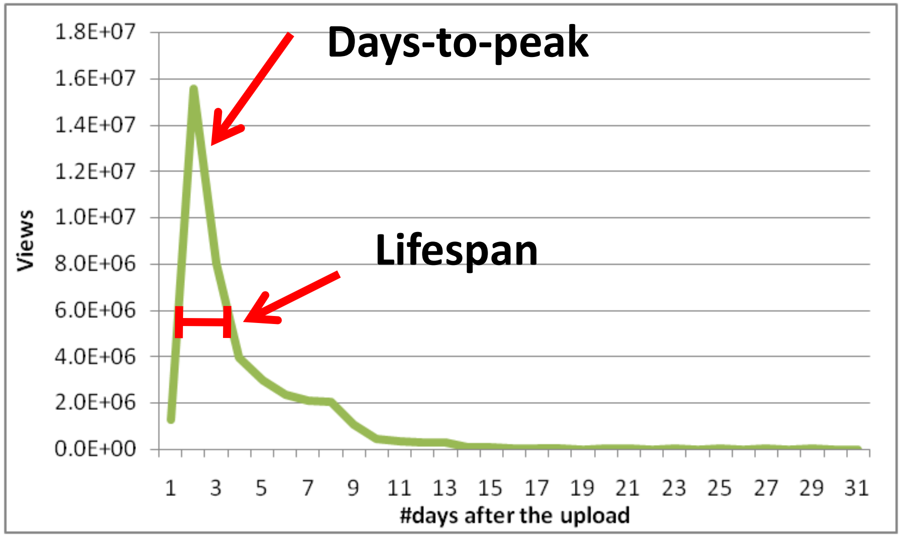
- Observations agree with existing studies including the study on Google's dataset
  - Short title, Short duration.
- Less biased.

Observation I

- *The days-to-peak and the lifespan of viral videos decrease over time.*

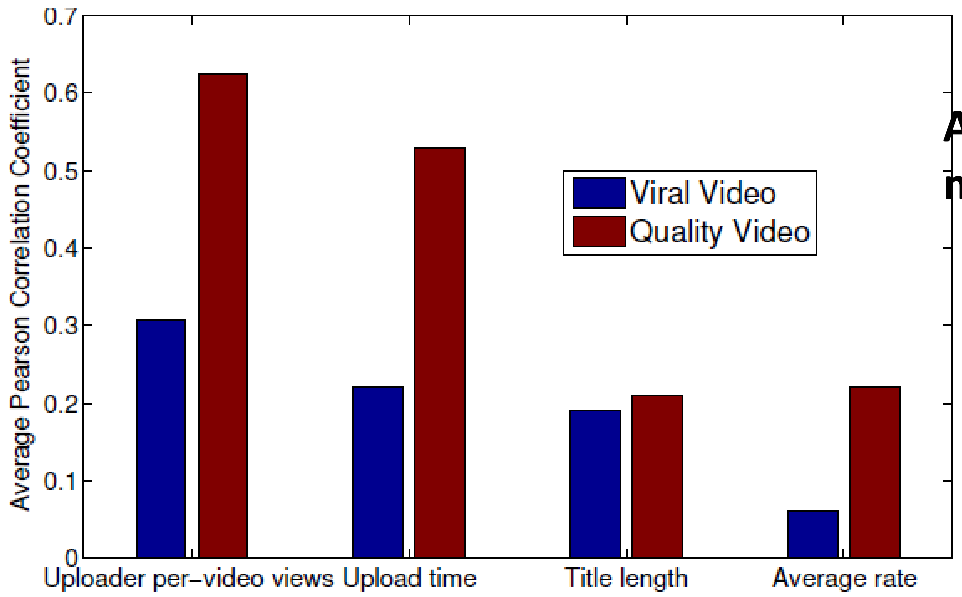
Table 4: Evolution of viral videos.

Statistics	2010	2011	2012
Days-to-peak Median	24	14	9
Lifespan Median	8	6	3



Observation II

- *The popularity of the uploader is a more substantial factor that affects the popularity than the upload time.*
- Upload time is believed to be the most important factor in background videos[Borghol et al. 2012], coined as First-mover advantage.



An example: official music videos

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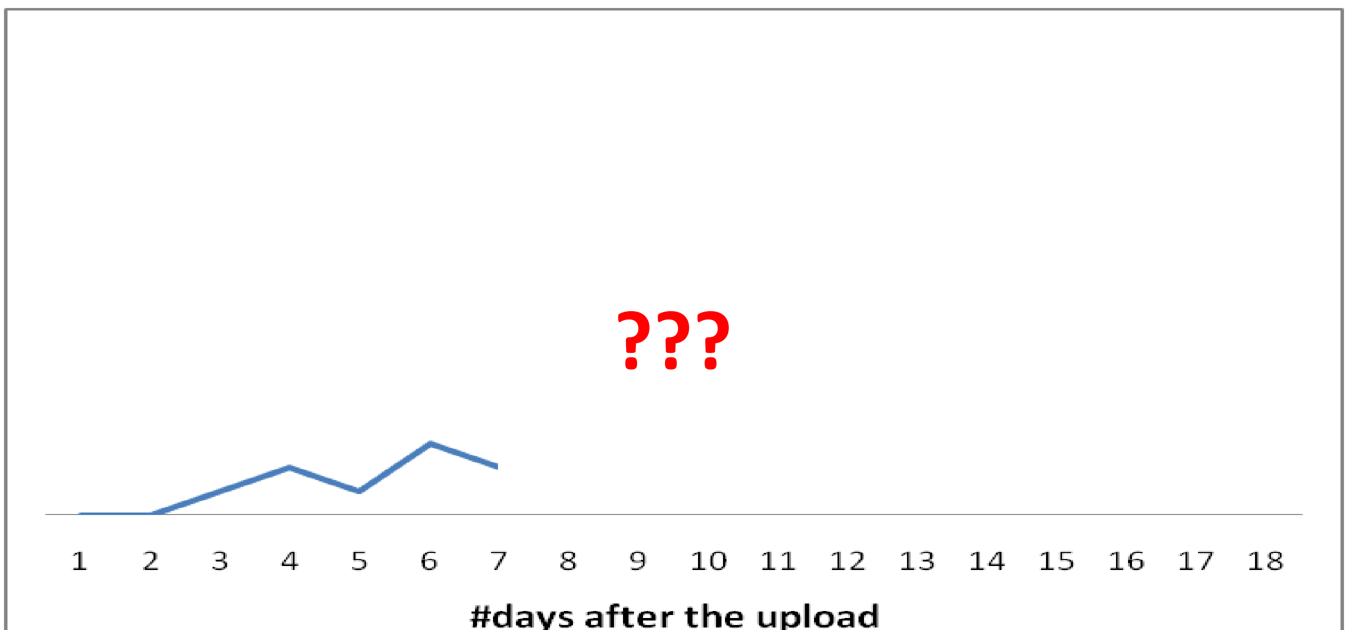
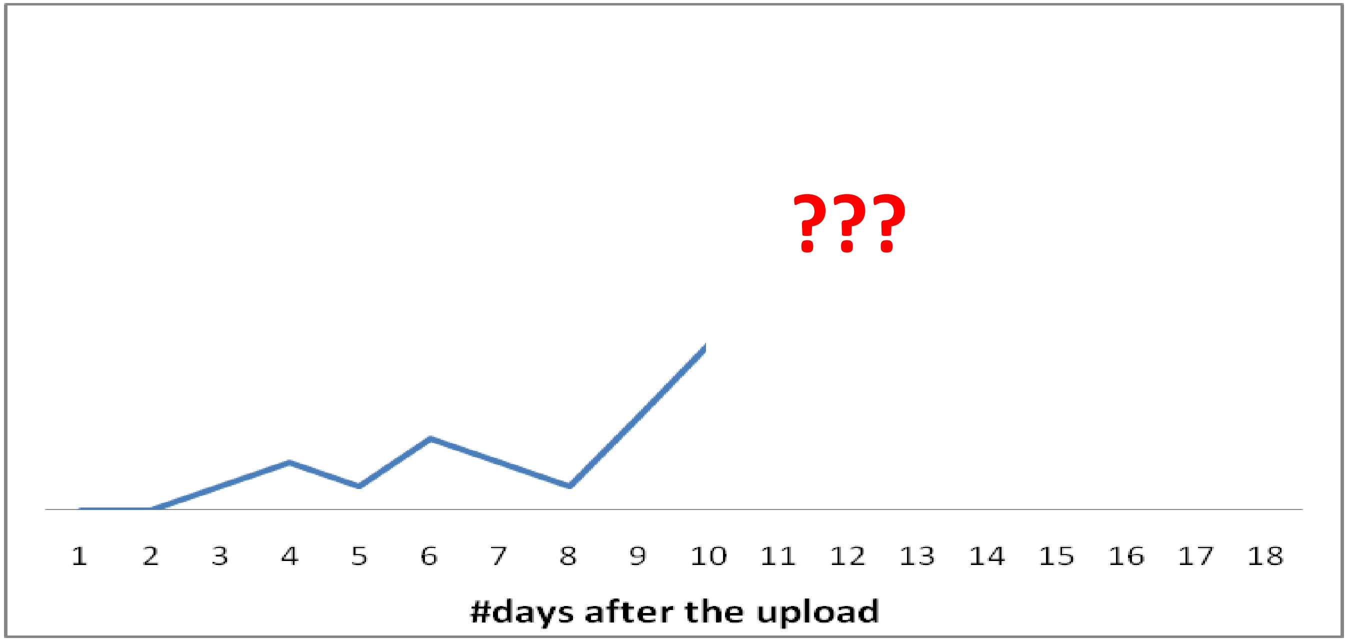
Peak Day Prediction

- Forecast when a video can get its peak view based on its historical view pattern.



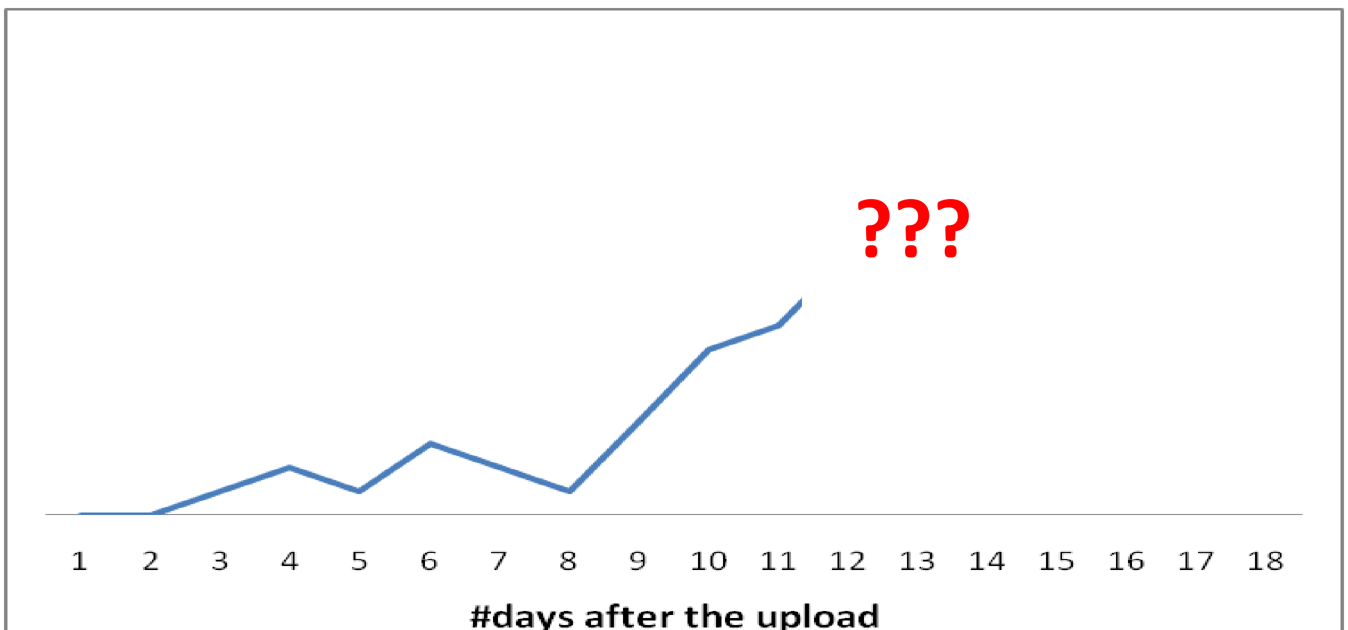
Peak Day Prediction

- Forecast when a video can get its peak view based on its historical daily view pattern.



Peak Day Prediction

- Forecast the date a video can get its peak view based on its daily view pattern.



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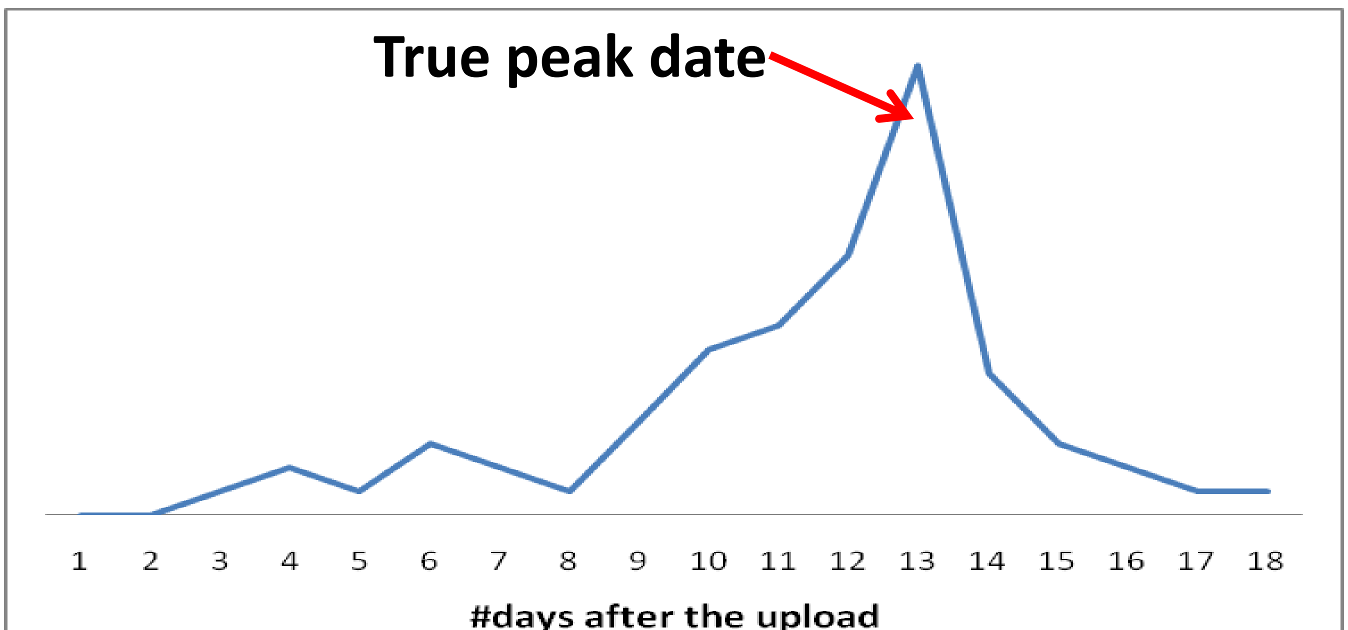
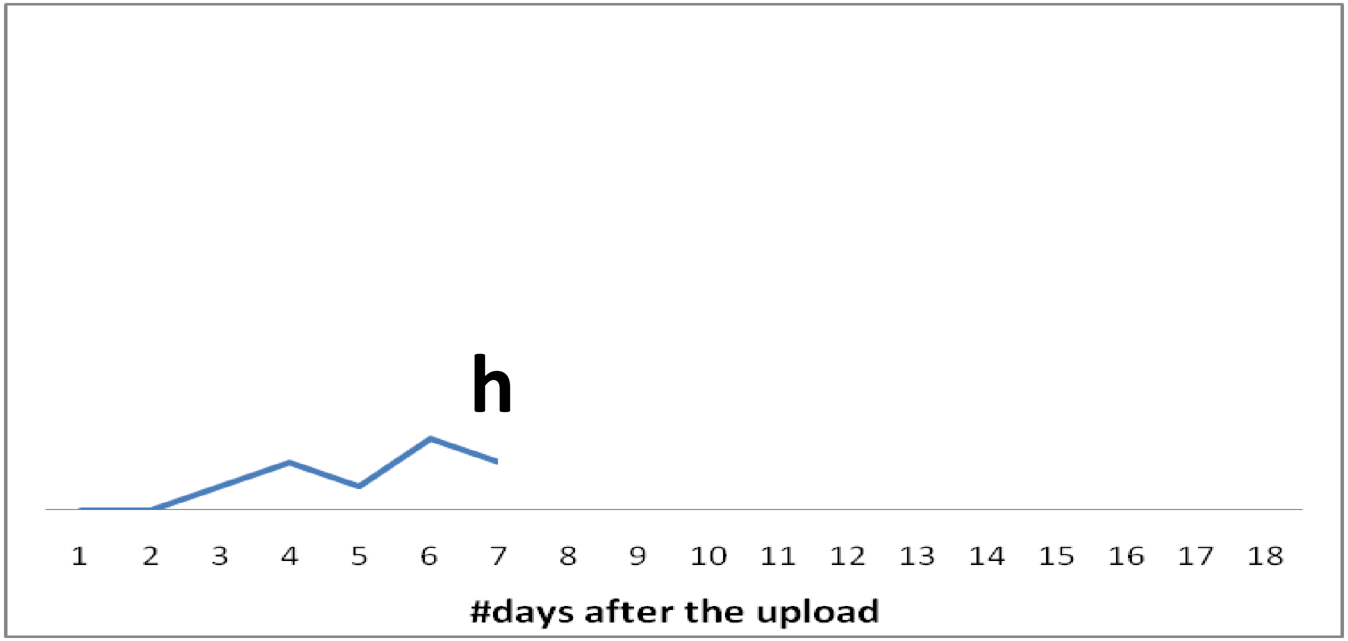


Peak Day Prediction

- Forecast the date a video can get its peak view based on its daily view pattern.
- This application is **significant** in supporting and driving the design of various services:
  - Advertising agencies: determine timing and estimate cost
  - YouTube: recommendation
  - Companies/Politicians: respond viral campaigns

HMM Model

- Model daily views using HMM model:
- Two types of states:
  - hibernating → less views
  - active → more views



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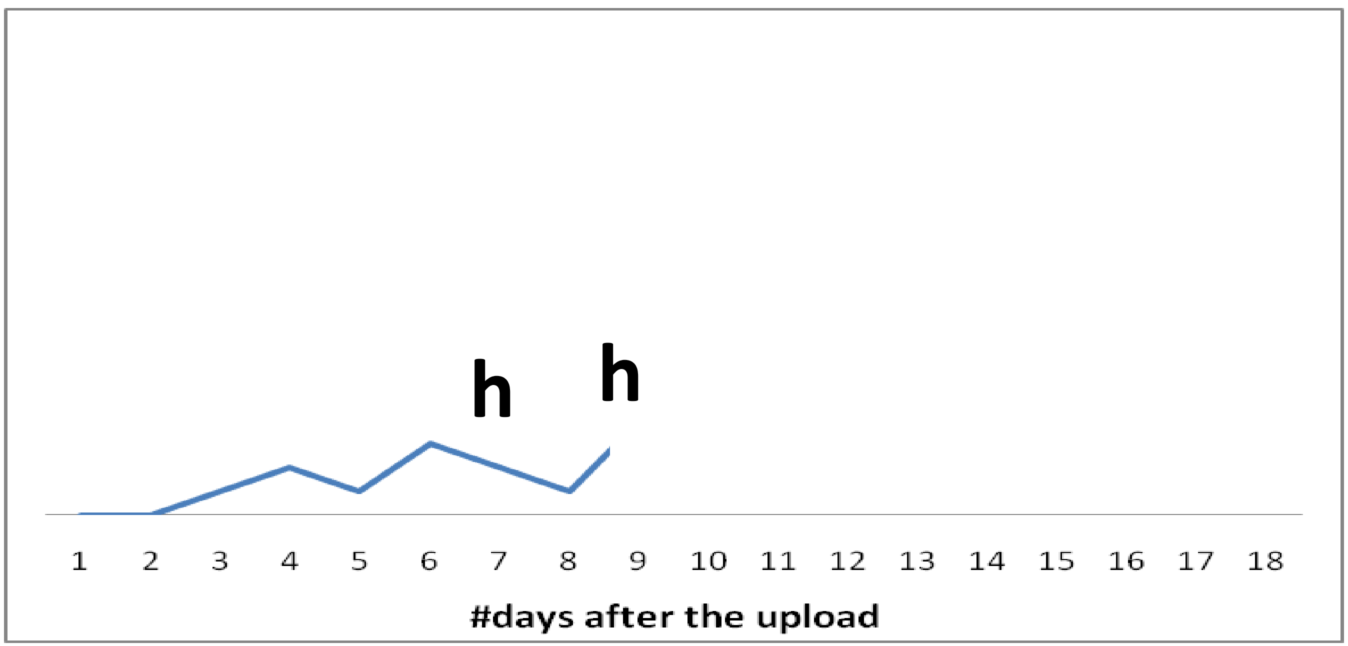

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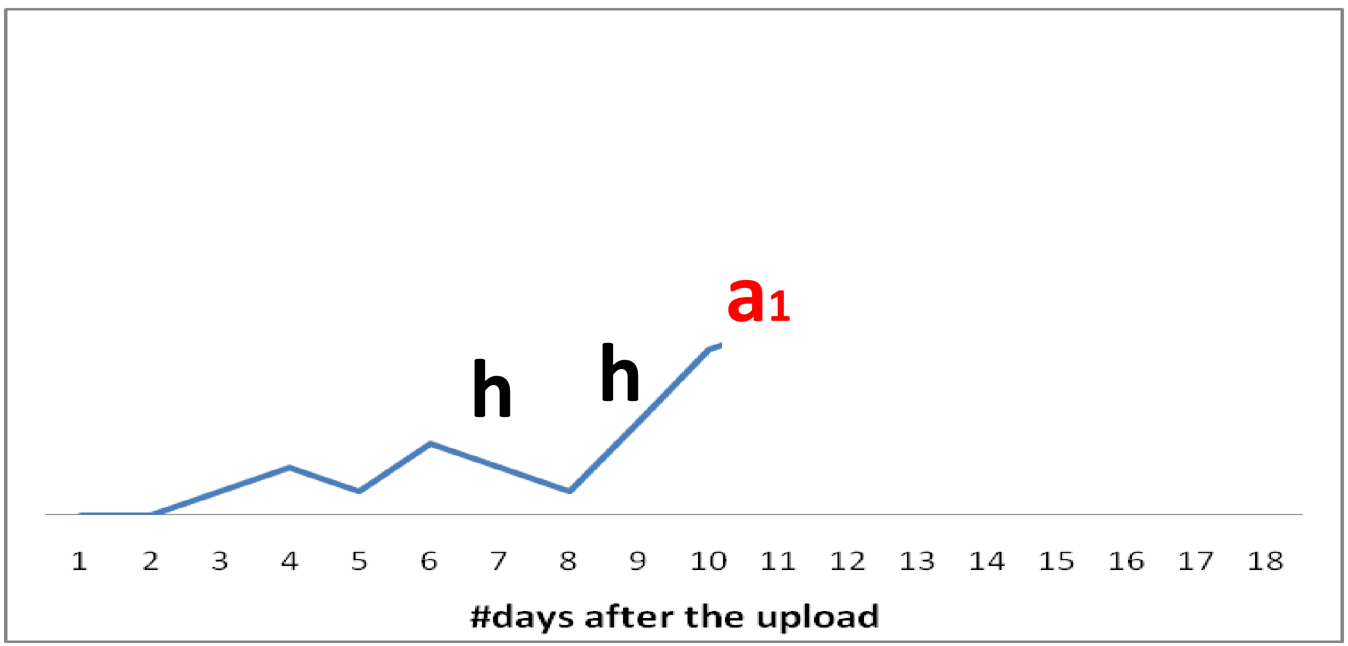

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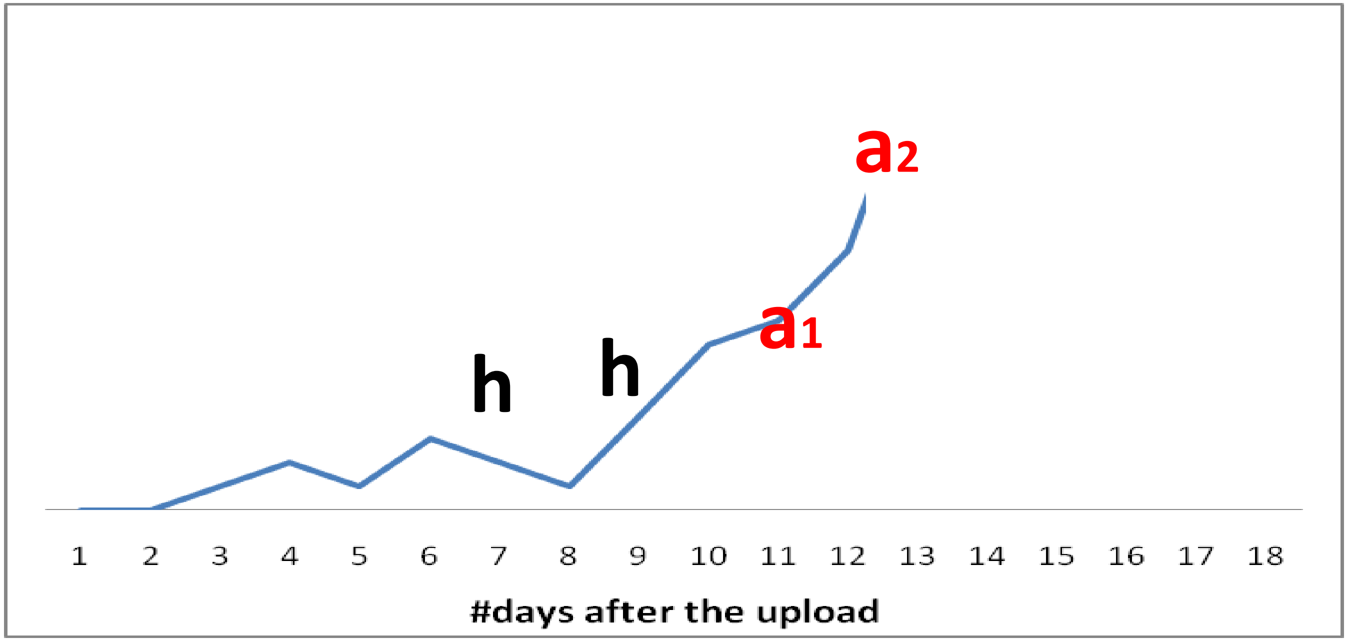

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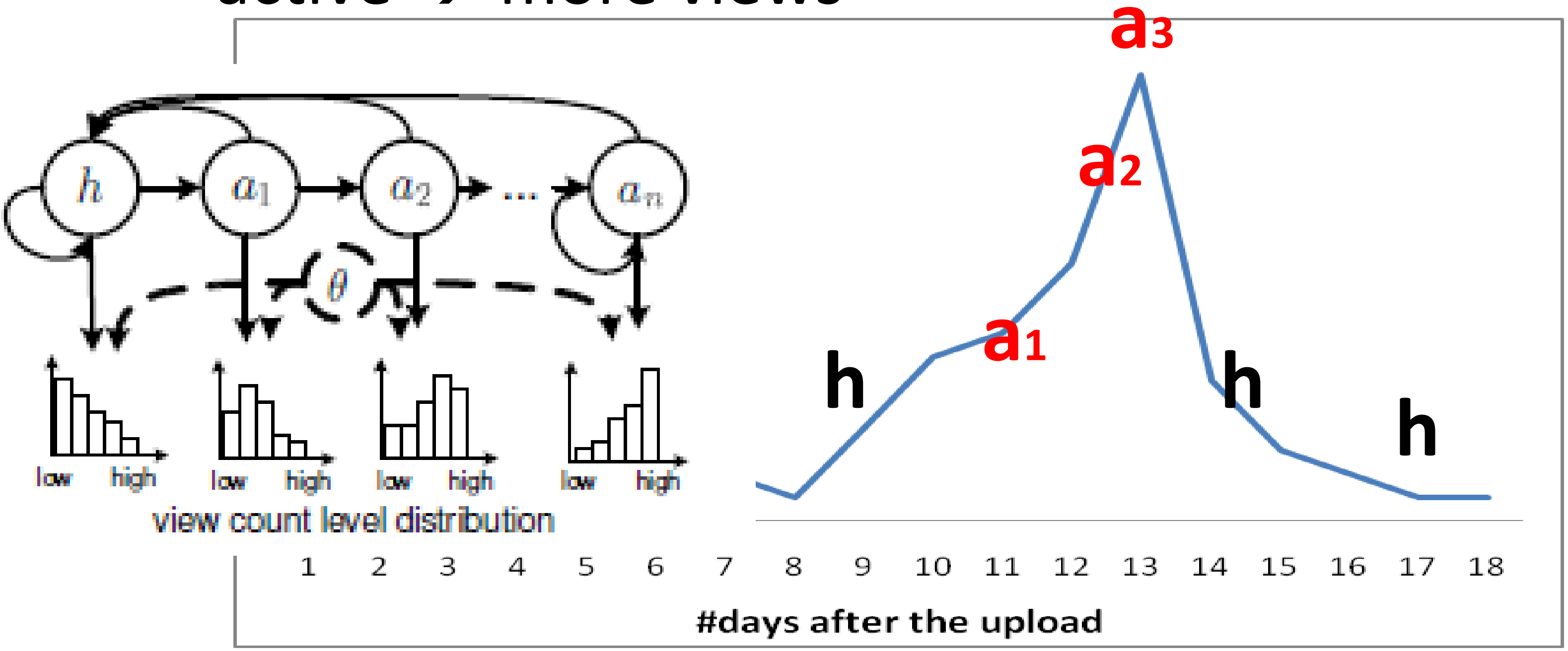
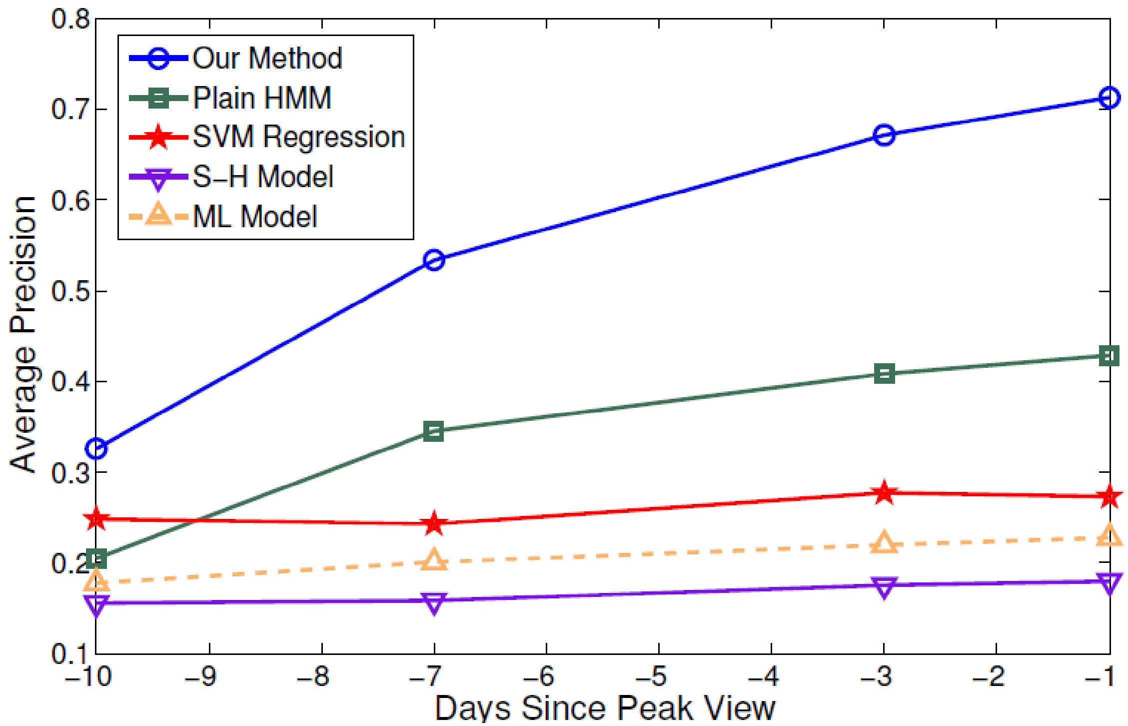


HMM Model

- Model daily views using HMM model:
- Two types of states:
  - hibernating → less views
  - active → more views
- Novel modifications:
  - Incorporate metadata in the prediction. Other work only use the pure view count [Pinto et al. 2013].
  - Smooth transition probability by a Gaussian prior.

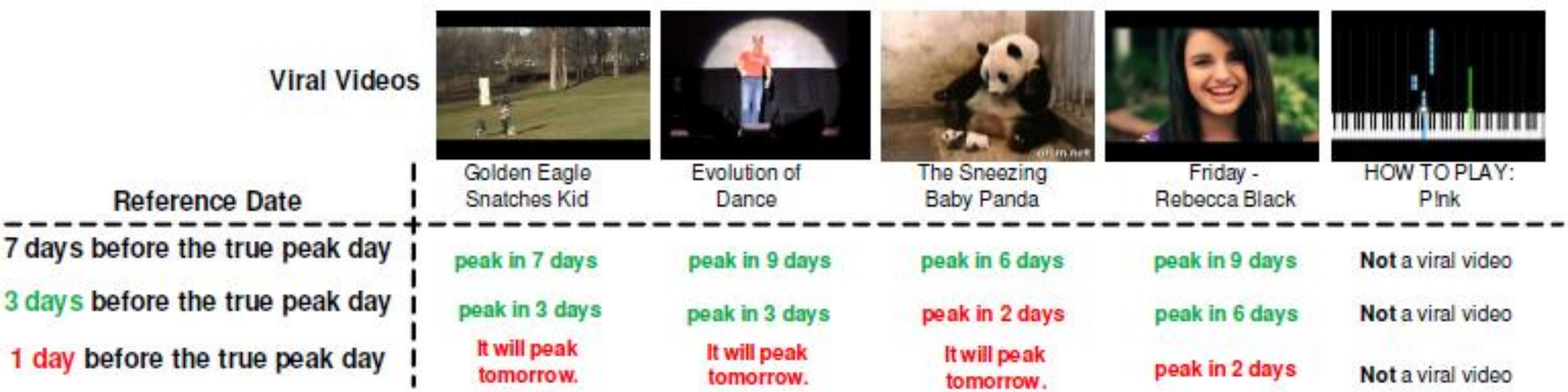
Experimental Results



Considering **metadata** in peak day prediction is instrumental.

Result cont.

- Early warning system for viral videos.
- Detect viral videos and forecast their peak dates.



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Conclusions

- A few messages to **take away from this talk**:
  - CMU Viral Video Dataset is by far the largest open dataset for viral videos study.
  - This paper discovers several interesting characteristics about viral videos.
  - This paper proposes a novel method to forecast the peak day for viral videos. The preliminary results look promising.

References

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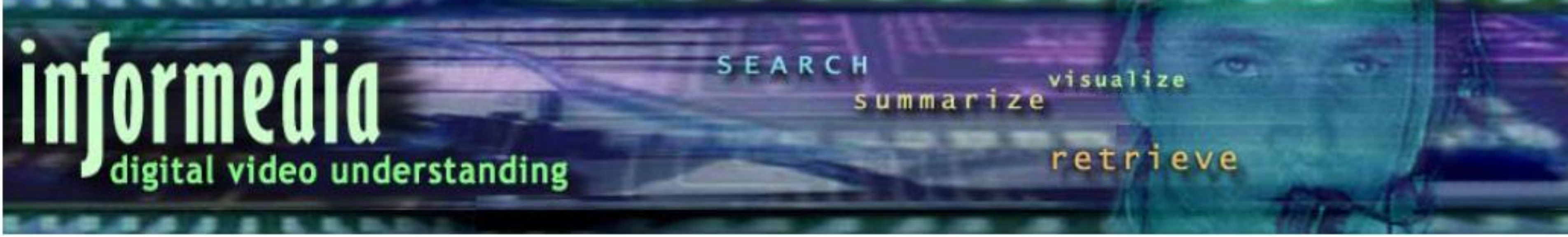
informedia
digital video understanding
SEARCH
summarize
visualize
retrieve

THANK YOU.
Q&A?