The Lifecycle of a Youtube Video: Phases, Content and Popularity

Honglin Yu, Lexing Xie & Scott Sanner, Australian National University, NICTA

1 The Problem

- How to describe and measure popularity over time?
- How to better predict popularity?

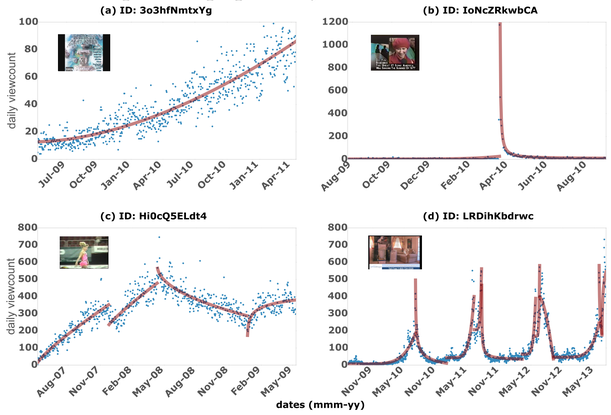


Figure 1: The complexity of viewcount dynamics: the lifecycles of four example videos. Blue dots: daily viewcounts; red curves: phase segments found by our algorithm. (a) A video with one power-law growth trend. (b) A video with one power-law decay. (c) A video with many phases, including both convex and concave shapes - this video contains a gymnastic performance. (d) A video with seemingly annual growth and decay - this video demonstrates how to vent a air-conditioner, and reaches peaks during each summer. *Viewcount shapes such as (a) and (b) are explained by Crane and Sornette's model [PNAS 2008], but (c) and (d), and many more like them, are not.*

2 Main Contributions

- New representation: popularity phases.
- New method: phase extraction algorithm from popularity history.
- A large-scale, longitudinal measurement study of popularity.
- Better prediction of future popularity using phase representations.

3 Phase Detection

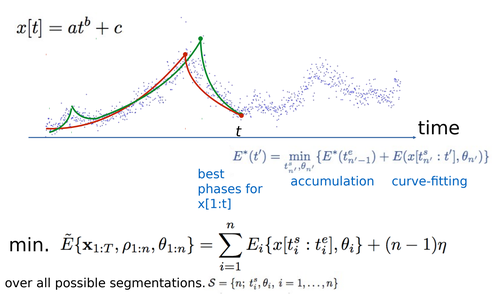


Figure 2: The phase detection algorithm. 1) Fits a generalized power-law shape for each phase; 2) Finds the best segmentations for phases, with a trade-off in fitting error and the number of phases.

Code/Dataset: `https://github.com/yuhonglin/ytphasedata`

4 Dataset

172,841 videos from 184 million Tweets Jun–July, 2009.

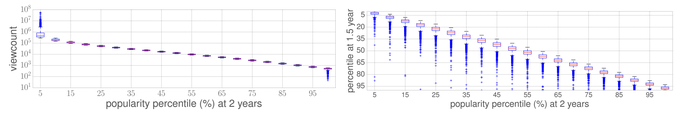


Figure 3: Left: Boxplots of video viewcounts at $T = 735$ days, for popularity percentiles quantized at 5% each. Viewcounts of the 5% most- and least- popular videos span more than three orders of magnitude, while videos in the middle bins are within 30% views of each other. Right: The change of popularity percentile from 1.5 years (y-axis, from 0.0% to 100.0%) to 2 years (x-axis, in 5% bins). While most videos retain a similar rank, videos from almost any popularity at 18 months of age could jump to the top 5% popularity bin before it is 24 months old (left most boxplot).

5 Observations

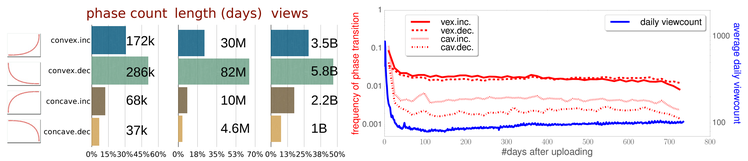


Figure 4: Left: Four types of phase shapes and their basic statistics; Right: Red curves are the probability of a video having a new phases in 15-day intervals over time, broken down by phase types. Blue curve is the average daily viewcount.

Phase, Video Type and Popularity

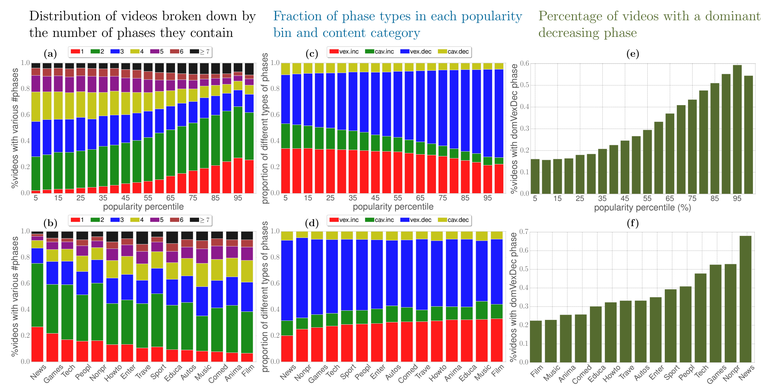


Figure 5: Left: Percentage of videos broken down by the number of phases they have, over (a) popularity percentile and (b) content categories. Middle: Percentage of the four phase types, broken down by (c) popularity percentile and (d) content categories . Right: Percentage of videos with a dominant convex-decreasing phase ($\geq 90\%T$), broken down by (e) popularity percentile and (f) content categories. A general trend is that popular videos and entertainment content (e.g. *music* videos) have more phases overtime, and more than half of *news* videos and the least popular videos have one dominant decreasing phase.

Concave phases

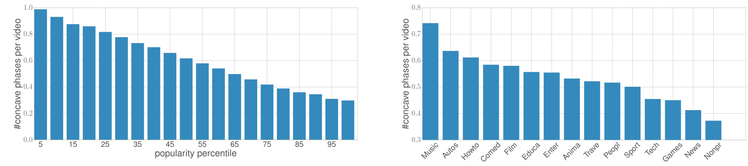


Figure 6: Popular and *entertaiment* videos have more concave shapes. Such phase shape cannot be generated from Crane-Sornette model, our ongoing work focus on a generative model that can explain all phase shapes.

Phase types of the most popular videos

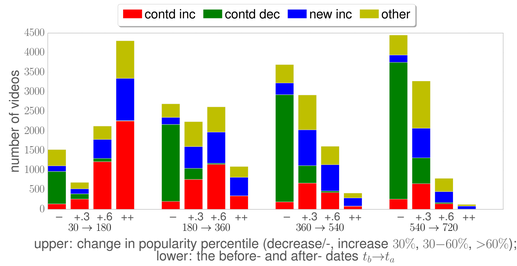
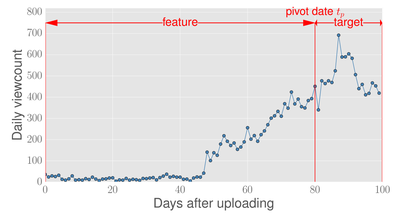


Figure 7: Phase type and popularity evolution for the top 5% videos over time. We can see that videos that have *jumped* by more than 30% in popularity either have new phases or have been in a continuously increasing phase.

6 Viewcount Prediction



- Target: $\chi^* = \sum_{\tau=1}^{\Delta t} x[t_p + \tau]$
- Prediction: $\hat{\chi} = \sum_{\tau=1}^{t_p} \alpha_\tau x[\tau]$
- Measure: normalized MSE, $\epsilon = \frac{1}{\Delta t |\mathcal{V}|} \sum_{v \in \mathcal{V}} (\chi^* - \hat{\chi})^2$

- Baseline : Multi-linear regression
- Phase-aware : Use phase feature to group videos and train separate models for each group.

Phase-informed prediction consistently out-perform baseline approach across all phase types and task settings.

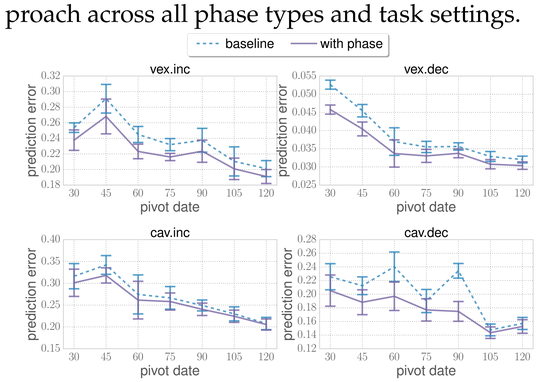


Figure 8: Mean normalized MSE for the baseline and phase-informed prediction over different pivot dates (x-axis) for videos with less than 5 phases, broken down by the shape of the last phase of $\mathbf{x}_{1:t_p}$, Δt=15 days

.