Classifying Derivative Works with Search, Text, Audio and Video Features

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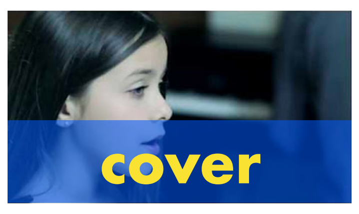
1. Motivation

Goal: to find derivative works of popular songs posted online.

Music videos and their derivatives are hugely popular on YouTube and other services.

Audio Content (AC) and **Video Content (VC)** are independent, and both important:

youtu.be/rYEDA3JcQqw
AC: Original audio
VC: Official music video



youtu.be/a7UFm6ErMPU
AC: Cover (new arrangement)
VC: Live (performance)

youtu.be/n7xoVgmQVDQ
AC: Live (perf. by orig. artist)
VC: Live (concert)

youtu.be/8WCb58e14Mo
AC: Remix (samples orig.)
VC: Still image

youtu.be/LP4kBLxW5RQ
AC: Original audio
VC: Lyrics (as slideshow)

youtu.be/oGqFexs3xkk
AC: Original audio
VC: Dance performance

Problem: text search for derivatives gives many errors: a search for "covers" often gives remixes; a search for "live" can give covers; etc.

Solution: build a system to re-classify search results based on **search** rank, **text** [i.e., video title], **audio** and **video** features.

2. Related work

Techniques exist to identify specific types of derivatives:

Fingerprinting: peaks in audio signal spectrum are robust to noise and can be used to identify exact copies of audio.

Remix detection: look for any matching fingerprints, possibly time- or frequency-distorted.

Cover song detection: characterize chord and/or melody structure, then look for matches.

Live song identification: use a variation on fingerprinting that is feasible if artist is known.

But these methods were not designed and are not guaranteed to *distinguish* between types of derivatives.

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3. Proposed system

Inputs: keyword list and query song/artist

Keywords
"choreo"
"concert"
"cover"
"dance"
"guitar"
"karaoke"
"live"
"lyrics"
"piano"
"remix"
"tutorial"

Query
'Gotye Featuring Kimbra, "Somebody That I Used To Know" [keyword]'

YouTube

All search results
```
8UVNT4wvIGY, d9NF2edxy-M, DqRC5tquyU0,
6YzGOq42zLk, IAVL1JBjtoU, vOlF5YRV8Ow,
doJbORheLzw, te0Q1XwaTyo, hOKuAigsrec,
00KnR6CltzE, _g9bBO1lfu8, UzSbbzYGECQ...
```

Extract features:
- Search rank
- Text features
- Video features

"STV"
SVM classifier

Initial predictions
```
8UVNT4wvIGY, orig./orig.
d9NF2edxy-M, cover/live
DqRC5tquyU0, orig./lyric
6YzGOq42zLk, live /live
IAVL1JBjtoU, orig./dance
...          ( AC / VC )
```

AC exemplars
```
Best orig.: 8UVNT4wvIGY
Best live : 8V6241UyHOE
Best remix: -d_PZikUT2I
...
```

Extract audio features
(compare audio to class exemplars)

"STVA"
SVM classifier

Refined predictions
```
8UVNT4wvIGY, orig./orig.
d9NF2edxy-M, cover/live
DqRC5tquyU0, orig./lyric
6YzGOq42zLk, live /live
IAVL1JBjtoU, remix/dance
...          ( AC / VC )
```

Phase 1: make initial prediction of AC and VC for each video.

Treat the highest-confidence examples for each AC category as **class exemplars.**

Phase 2: compare audio files to class exemplars, and obtain **refined predictions**.

4. Features

To estimate the AC and VC of videos, we use an SVM with a multi-modal set of four features:

Search: a video can appear in several keyword searches. We use a video's rank in each search. E.g., a dance video might have ranks:

Keyword:	main	choreo	concert	cover	dance	guitar	..	tutorial
Rank:	22	1	361	–	3	–	..	–

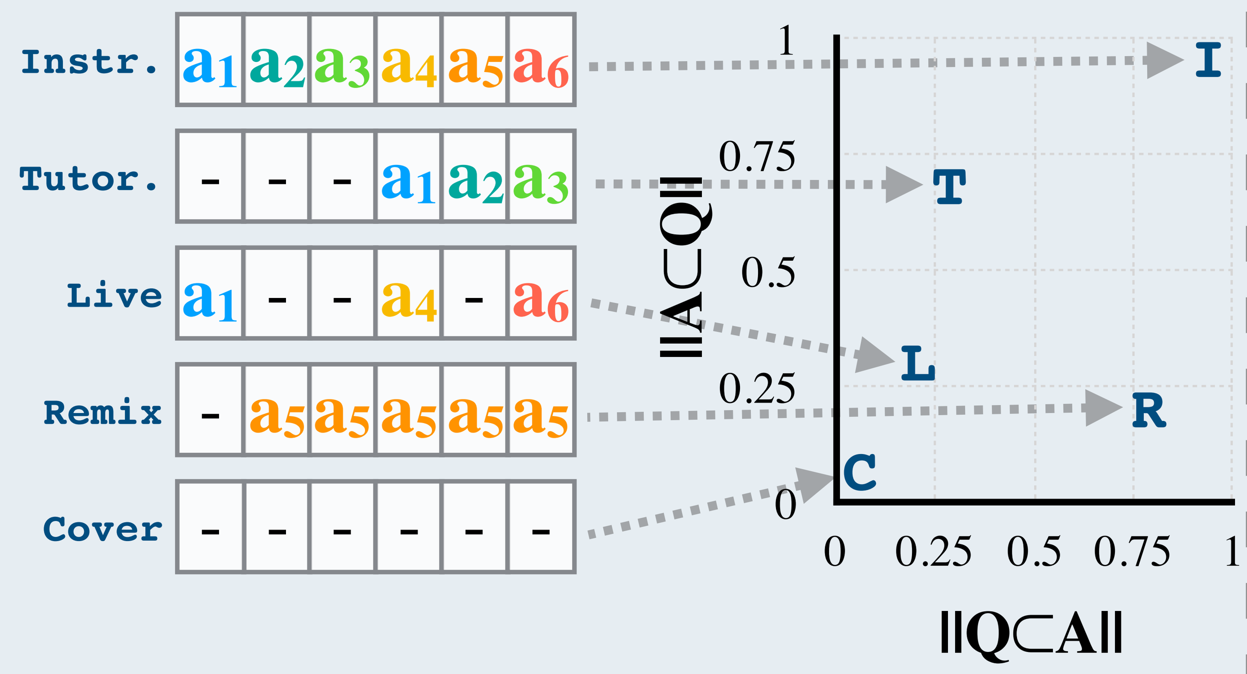
Text: words that appear in many titles are likely to relate to AC or VC: e.g., "acoustic"→`cover`, "tour"→`live`, "vs"→`remix`, etc. From an unlabelled set of ~150,000 video titles, we learn latent topics. We can then convert each title to a "topic strength" vector. To help the learning process, we detect terms from dictionaries of places, names, instruments and genres.

Video: common video features (e.g., brightness, colour variance, optical flow). To detect lyrics, we do text-recognition using *Tesseract*.

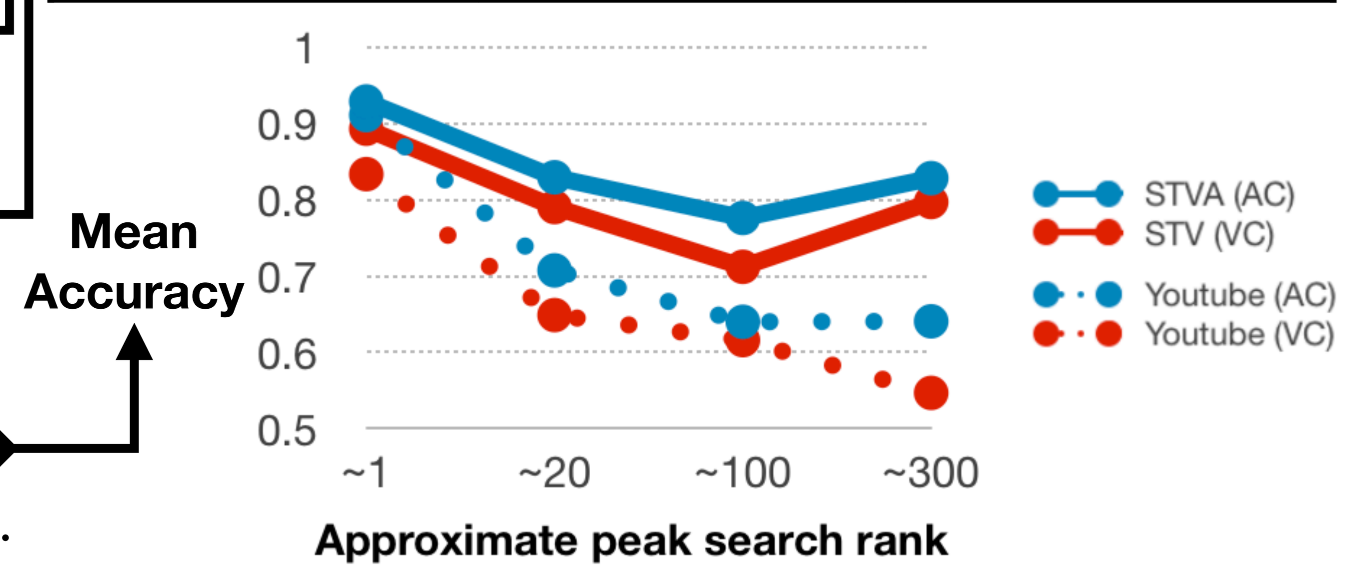
Audio: we use audio fingerprinting to match 10-second snippets to the original song. The distribution and quality of matches found is different for different types of derivatives.

Original audio A, *cut into chunks:* $a_1\ a_2\ a_3\ a_4\ a_5\ a_6$…

We characterize each song Q with two values:
- the fraction of snippets in song Q ($q_1q_2q_3q_4$...) that have a match in the original, A: $\|Q\subset A\|$
- the fraction of snippets in song A ($a_1a_2a_3a_4$...) that have a match in song Q: $\|A\subset Q\|$



Features:	AC accuracy	VC accuracy
S(earch)	0.699	**0.705**
T(ext)	**0.781**	0.690
V(ideo)	0.416	0.505
A(udio)	0.623	0.552
ST	0.822	0.767
STV	0.815	**0.804**
STVA	**0.847**	0.781
YouTube Baseline	0.746	0.685



5. Evaluation

Data: We discovered 160,000 derivatives of the BillBoard Top 100 songs of 2012. We labeled 562 videos related to 10 unique songs, and used the rest (titles & search ranks) for unsupervised training.

Ground truth: manually annotated **AC** and **VC**:

- **6 AC categories**: `official, cover, instrumental, live, remix, tutorial`.
- **9 VC categories**: `official, dance, karaoke, live, lyrics, slideshow, still image, tutorial, other`.

Baseline: a decision tree (DT) using peak search rank from YouTube searches. E.g., if video has the highest rank for the "remix" keyword search, then **AC→`remix`** and **VC→`still`**.

Results:

- <u>Text features</u> alone match the performance of the YouTube baseline.
- Combining all features (<u>STVA</u>) in two-phase approach, we surpass baseline by 10%.
- Our system is also **more robust than baseline**: classification of deep search hits still accurate.