BeaverDam: Video Annotation Tool for Computer Vision Training Labels

by

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Committee in charge:

Professor Kurt Keutzer, Chair Professor Only Somewhat Important Guy

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BeaverDam: Video Annotation Tool for Computer Vision Training Labels

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Anting Shen

Abstract

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Your abstract should be limited to 350 words. If it is longer, ProQuest will truncate and/or edit it so that it is less than 350 words. This is a very boring dissertation that nobody will probably ever read.

blah blah	blah blah	blah	blah.	Blah											
blah blah	blah.														

And so it goes...

Professor Kurt Keutzer Thesis Committee Chair

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Introduction

Deep learning applications in recent years have come to require rapidly growing amounts of labeled training data. Often, accuracies can be boosted by adding data as much as by spending years on algorithmic development. For example, on the VOC07 benchmark, Faster-RCNN [?] with VGG-16 was able to eliminate 27.5% of errors in the much older R-CNN [?] backed by an equally old neural network architecture (mAP improved from 58.5 to 69.9). However, simply by including additional data from VOC12 and COCO, 29.5% of the remaining error was eliminated (mAP improved from 69.9 to 78.8). Therefore, for real-world application development, data can be cheaper and more effective than scientists. While many existing tools support image classification – it is even built into Amazon Mechanical Turk (MTurk) – and some tools support bounding box labeling in images, few tools exist for frame-by-frame labeling in videos. VATIC [?] stands out as being one of the best, as not only does it make high quality annotations one of its main goals, but also cost and scalability.

My work borrows and improves upon many concepts and results from VATIC's user studies, but I focus on an additional goal that is extremely important in creating datasets for real applications. That goal is researcher happiness. Although VATIC extensively tested its "User Interfaces", I argue in chapter 2 that both the annotators and the experimenters are users, and the interfaces should be smooth for both when creating a tool.

Then, in chapter 3, I discuss my take on VATIC's User Interface principles for the annotator, and improvements upon them.

I also release all related code for BeaverDam, my video labeling platform, on Github.¹

Related Work

Static image annotators

Vatic, LabelMe, etc

Things other people cite

¹http://github.com/antingshen/beaverdam

Experimenter Interface

During our investigation, we had many frustrating experiences with existing research tools in this area. These included installation issues, configuration issues, and dealing with unintuitive and undocumented interfaces. For example, there are dozens of open issues without solutions on the VATIC GitHub, and its installation script fails at multiple points on a brand new Ubuntu box. Due to preciousness of researcher's time, we believe the ability for researchers to test and iterate quickly is just as important as worker speeds when it comes to video annotation. Therefore we have placed improving the experimenter's experience as one of the main goals of this work.

2.1 Interface for researcher

For a basic user creating a crowdsourced video dataset using the default configurations we used, BeaverDam provides a streamlined interface. We provide a setup script that is tested on clean installs of Ubuntu 14.04 and Ubuntu 16.04. In comparison, VATIC was tested on an unspecified Ubuntu installation with exact Apache and MySQL installs, and while the install script claims that it should work on any operating system in theory, installation is difficult in reality. Additionally, our install script configures everything from Nginx and TLS to database config and backups. The user only needs to place their keys and

credentials in the locations specified in our documentation. While a containerization system such as Docker would have also solved VATIC's issues and ensure future compatibility, we felt that the additional complexity is not worth it, as many of our users in the research community are unfamiliar with Docker.

To use BeaverDam after installation, we provide a web interface for researchers to easily add and view videos and jobs. We feel that this is superior to VATIC's command line based approach, as the number of flags needed to specify various configurations was overwhelming. However, to allow experimenters to load large number of videos or perform other tasks programatically, BeaverDam also provides a Python shell interface, backed by Django, to expose every functionality through Python.

Lastly, as BeaverDam is HTML5 video based, no frame extraction step is necessary. H.264 encoded videos will work without preprocessing. However, we do provide scripts to convert these videos to images with matching annotations to feed into machine learning tools if desired.

2.2 Decoupled modules

Comparison with microservice

Serving videos

Hosting annotator (ansible)

Crowdsourcing platform independence

Tracking module

2.3 Patterns

Django backend

Patterned frontend (MVC, event-based)

2.4 Dependencies

Few dependencies (sqlite)

Easily restore state

Uses newer technologies

2.5 Security

DB Backup

Authentication enables decoupling, web admin

Other standard procedures, HTTPS & HSTS, CSRF, clickjacking

Annotator Interface

Intro & our method of user studies (not as good as VATIC though)

3.1 Keyframe scheduling & Multiple object annotation

Keyframe viewer when on custom schedule

3.2 Video playback for maintaining identity

Importance of playback

Video loading issue

HTML5 video advantages

3.3 Reducing clicks

Create by default

Object selector

Keyboard shortcuts

3.4 Handling frame exit/enters

Border padding

Allow out-of-border boxes

3.5 Micro vs Macro tasks

Comparison from existing literature

Proposal advocating for micro-tasks in video labeling

Extensible task structure

3.6 Interpolation & Tracking

Conclusion

Ha! I'm done!

References

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