

Building Usage Profiles Using Deep Neural Nets

Domenic Curro, Konstantinos G. Derpanis, Andriy V. Miranskyy
Department of Computer Science, Ryerson University, Toronto, Canada
{d2curro, kosta, avm}@scs.ryerson.ca

Motivation

Objective

Build a software usage profile from tutorial videos hosted online

Challenges

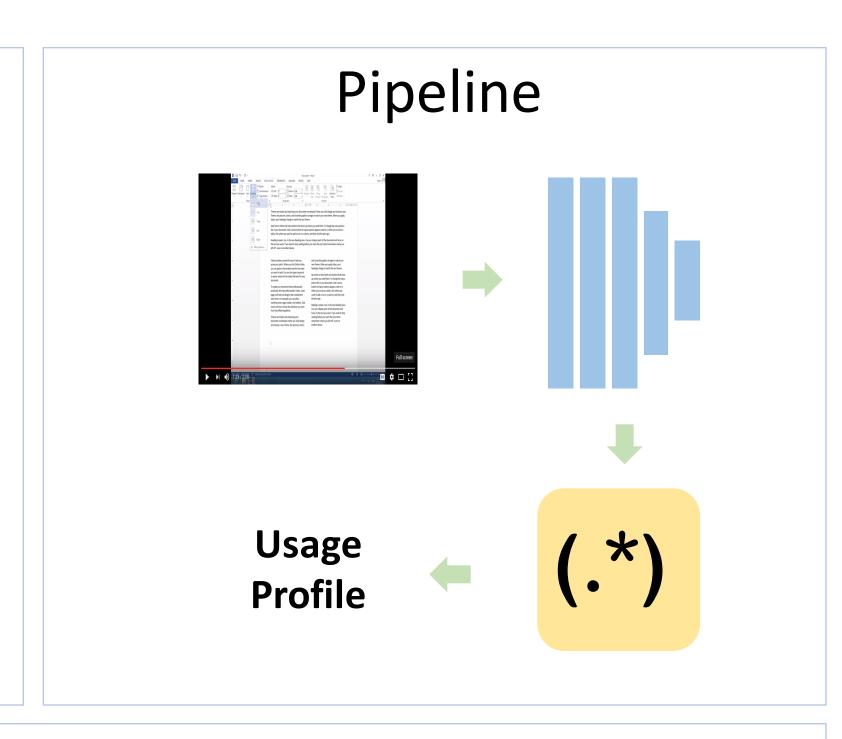
Individual user actions are a latent variable within video frames

Prior Work

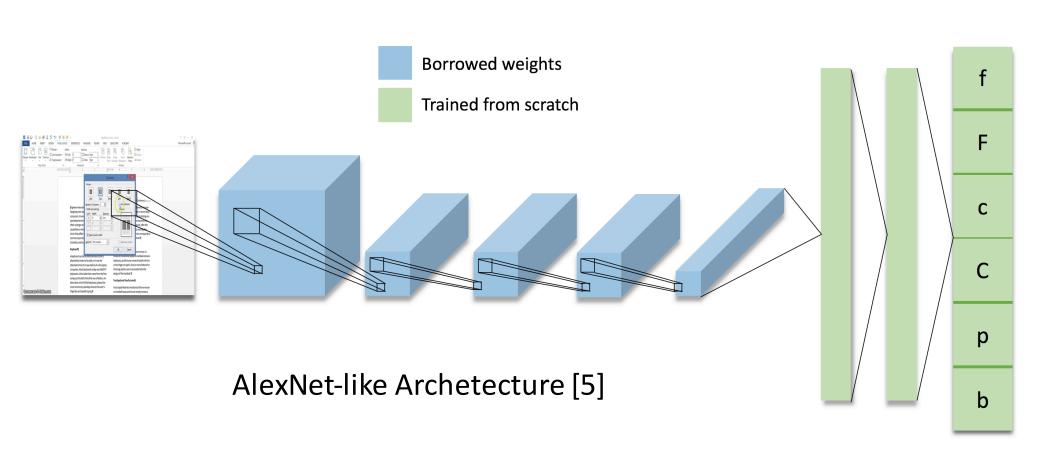
Video recordings have been used in ethnographic studies, for user experience [1]. Automatic tools exist that can locate specified images on screen to some threshold [2]. There are suggestions that DCNNs can be used in source code analysis [3]. To the best of our knowledge, nobody has considered extracting user actions from UI-based images

Contribution

Automatic proof-of-concept pipeline for generating usage profiles from raw video data



Action Sequence



- Pre-trained network with ImageNet [4] weights
- Sufficiently trained with very few examples per class
- Invariant to image noise, screen capture artifacts, various Word versions, screen resolutions, system fonts, system colours, and mouse occlusions

User Profile	Data Count	Apparent User Action
f	118	The font menu is open
F	46	The default font window is open
С	381	The columns drop down is open
С	396	The columns window is open
р	293	The page number drop down is open
b	39.5k	None of the above user actions is occurring
p	293	The page number drop down is open

Evaluating a video, a sequence of actions is collected

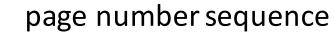
User Profile Prediction

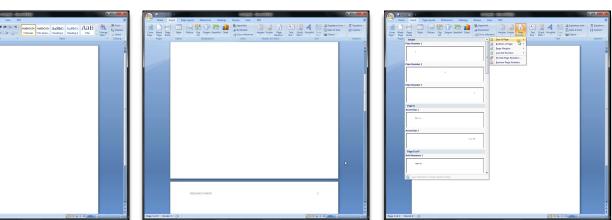


A sequence of user actions are matched against a series of regular expressions, selecting the appropriate usage profile

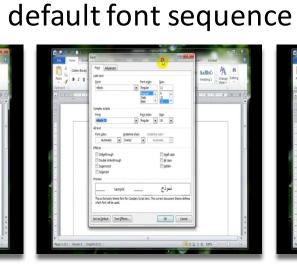
User Profile	Regular Expression	The user
α	f{r,}	changed font via the font menu
β	f{r,}F{r,}f{0,r}	changed their default font
γ	c{r,}	changed the column count via the drop down menu
δ	c{r,}[^cC]{0,r}C{r,}	changed the column count via the column window
ε	p{r,}	changed page numbering via the page number dropdown

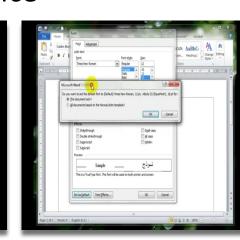
Results

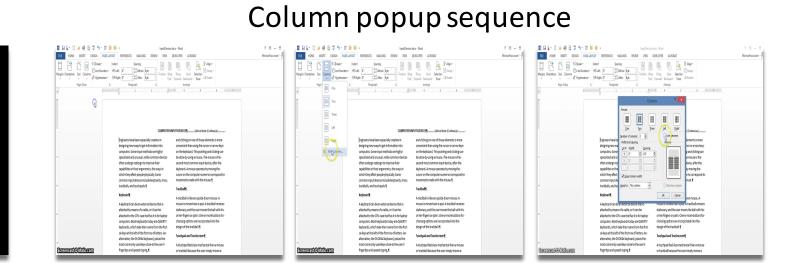




| Construction | Cons







Action Prediction Confusion Matrix

	b	f	F	С	С	р	Recall
b	38852	49	25	210	170	198	98.35%
f	27	86	2	0	3	0	72.88%
F	8	4	33	0	1	0	71.74%
С	34	0	0	347	0	0	91.08%
С	93	0	1	2	300	0	75.76%
р	39	0	0	0	1	253	86.35%
	99.49%	61.87%	54.10%	62.08%	63.16%	56.10%	precision
	98.91%	66.93%	61.68%	73.83%	68.89%	68.01%	F1-score

Individual Actions Mean F1-score (without **b**): 67.87%

Profile Prediction Confusion Matrix

	α	β	Υ	δ	η	Recall
α	4	1	1	0	0	66.67%
β	2	15	0	0	0	88.24%
Υ	1	0	75	2	2	93.75%
δ	0	0	4	54	0	93.10%
η	0	0	1	0	74	98.67
	57.14%	93.75%	92.59%	96.43%	97.37%	precision
	61.54%	90.91%	93.17%	94.74%	98.01%	F1-score
	80.16%	95.10%	97.25%	99.82%	99.79%	AP

Usage Profile Mean Average Precision: 94.42%

References

- 1. D. Socha, R. Adams, K. Franznick, and et al. Wide-field ethnography: Studying software engineering in 2025 and beyond. In 38th Int. Conf. on Software Engineering Companion, pages 797–802, 2016
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