PERCIVAL: Making in-browser perceptual ad blocking practical with deep learning

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Web pages compose content and ads from multiple domains

nytimes.com
Web pages compose content from multiple domains.
Ad network can sell the ad space to another network [Li et al.]
Why ad blocking?

INTRUSIVE ADS AFFECT USER EXPERIENCE AND PERFORMANCE ON EDGE DEVICES. [SHAO ET AL.]
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Ad content taking up a lot of screen space.
Why ad blocking?

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AD DISTRIBUTION CHANNELS HAVE BEEN USED TO DISTRIBUTE MALWARE. [XING ET AL.]
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ADVERTISERS TRACK USERS TO IDENTIFY THEM ACROSS WEBSITES. [LERNER ET AL.]
Existing Ad blocking solutions use handcrafted, crowd-sourced filter-lists like EasyList.
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Existing Techniques fall short

Filter-list based blocking can easily be broken – by changing the URL or page markup

There are a lot of redundant un-matched rules [Snyder et al.]

Updating the rules takes a lot of time [Iqbal et al.]
Perceptual Ad Blocking [Storey et al.]

Looks at the content of the ad
Perceptual Ad Blocking

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And not at the markup
Perceptual ad blockers examine content from a user’s perspective.

The intended audience for advertisements are humans and not the browser.
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Operate on rendered content
Existing perceptual ad blockers also fall short.

Ad blockers only look at high-level features like the Ad Choices logo or text in the image [Storey et al.]
Existing perceptual ad blockers also fall short

AD BLOCKERS ONLY LOOK AT HIGH LEVEL FEATURES LIKE AD CHOICES LOGO OR TEXT IN THE IMAGE [STOREY ET AL.]

OTHERS ARE PROHIBITIVELY LARGE AND SLOW FOR PRODUCTION DEPLOYMENT [SENTINEL ET AL.]
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WORK AT THE EXTENSION LAYER [AD HIGHLIGHTER, STOREY ET AL.]
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PERCIVAL looks at the entire ad and non-ad content through the lens of a convolution neural network (CNN) to filter ads.
Overall Architecture of PERCIVAL in the browser.

PERCIVAL runs in the rendering engine of the browser.
PERCIVAL intercepts all visual content obtained during page execution and blocks ad content
Deep CNNs can beat humans on ILSVRC

Error rate vs Year

Deep Learning

Human Error rate = 5.1
However
Slow inference times

Error rate vs Year

On 16 core Arm Cortex-A72 CPU

- 275ms [Liu et al.]
- 575ms [Liu et al.]
- 351ms [Liu et al.]
Running deep CNNs in the browser in real time is non-trivial. Need smaller models with high-accuracy. All the visual content must go through the CNN, so need to keep the browser responsive with efficient design.
PERCIVAL: Design Principles

- Run in the browser
- Run at a choke point
- Run in parallel
- Run fast and be small
Browser: Has two main processes.

| Browser Process | Main Thread | IO Thread |
|-----------------|-------------|-----------|
| Renderer Process| Main Thread | IO Thread |

Rendering Engine: BLINK runs in the renderer process

Principle 1: Run in the browser
BLINK: Converts code to pixels on screen
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• Parse the HTML to create the DOM tree
BLINK: Converts code to pixels on screen

- Parse the style sheets to determine how to display content
BLINK: Converts code to pixels on screen

• Use the DOM and CSS to create the layout tree.
BLINK: Converts code to pixels on screen

- Other operations like paint operations, encode draw commands etc. to create display items.
BLINK: Converts code to pixels on screen

- Layout and paint stages create display items, which can have images that need decoding
BLINK: Converts code to pixels on screen

- Turn display items into bitmaps
BLINK: Converts code to pixels on screen

- Low level GPU primitives using SKIA
Finally: pixels on screen
With PERCIVAL: pixels on screen

PERCIVAL intercepts every image and blocks rendering of images classified as ads

Principle 2: Run at a choke point
Blink creates many worker threads to decode and raster in parallel.

| Worker thread 1 | Image Decode Task | Raster Task | PERCIVAL |
|------------------|--------------------|-------------|----------|
| Worker thread 2  | Image Decode Task | Raster Task | PERCIVAL |

In PERCIVAL, model inference is thread safe.
PERCIVAL: Implementation

#include<percival.h>

int callPercival(void* pixels){
    return model.predict(pixels);
}

void processImage(void* pixels){
    ......................
    ......................
    ......................
}
PERCIVAL: Implementation

We use SqueezeNet[landola et al.] as our base network. We refine the network to remove parameter heavy later layers as we gather and train with more data.

We use a singleton design pattern, where the model is loaded on the first invocation only.

The model inference is thread safe.
Evaluation: Performance

Mean render time impact on Alexa top 5000 URLs.
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Percival adds 4.55% or 178.23 MS to Chromium and 19.07% or 281.85 MS overhead to Brave.
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Evaluation: with a microbenchmark

First meaningful paint: Time it takes to display content on the user’s screen.
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We measure first meaningful paint on a static html page with 100 images.
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PERCIVAL adds 120ms to Chromium and 140ms to Brave
Evaluation: Accuracy on Facebook ads

Facebook has ads on the right-side column and sponsored content embedded in the feed.
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Metrics:
- TP: No of ads in right-side column or sponsored content blocked
- FP: No images in the remaining portion of the web page that PERCIVAL incorrectly blocks
- TN: No of images rendered in the remaining content
- FN: No of ads not blocked
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| Ads | No-Ads | Accuracy | FP | FN | Precision | Recall |
|-----|--------|----------|----|----|-----------|--------|
| 354 | 1,830  | 92.0%    | 68 | 106| 78.4%     | 70.0%  |
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Training a customized user model achieved a precision of 88.04% and a recall of 97.25%
Evaluation: Accuracy on non-English languages

- We tested on multiple non-English languages.

| Language | Accuracy | Precision | Recall  |
|----------|----------|-----------|---------|
| Arabic   | 81.3%    | 83.3%     | 82.5%   |
| Spanish  | 95.1%    | 76.8%     | 88.9%   |
| French   | 93.9%    | 77.6%     | 90.4%   |
| Korean   | 76.9%    | 54.0%     | 92.0%   |
| Chinese  | 80.4%    | 74.2%     | 71.5%   |

Side benefit of Deep learning, it generalizes well.
Adversarial attacks against PERCIVAL and defenses.

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PERCIVAL is smaller than the average web-page size and regular updating is not an issue.
More defenses and Future work

Client-Side Training:
If model is trained client side, every user has a different version of the model.
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Recent research on adversarial training is promising.
Madry et al.’s min-max optimization adversarial training demonstrates a strategy to deal with adversarial samples with security guarantees.
Conclusion

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PERCIVAL,
• has minor impact on browser performance,
• can block first-party ads,
Conclusion

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With PERCIVAL, it is practical to run deep learning based ad blockers directly in the rendering engine

PERCIVAL,

• has minor impact on browser performance,
• can block first-party ads,
• generalizes to other locales as well.
Thank you. Please direct your questions to zdin@ucdavis.edu