Continuous and Non-Intrusive Reauthentication of Web Sessions based on Mouse Dynamics

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(Re)Authentication

Credentials stealing is *not* an exceptional event

- *bad* current user with *good* credentials, possibly for a long time

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→ verify the user identity over the time

- by other means than credentials
- possibly non-intrusively

Behavioral biometrics

Non-intrusive continuous verification of the user identity
$\rightarrow$ Behavioral biometrics:

- keystrokes
- ...
- mouse trajectories

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Machine instrumentation for collecting biometrics may be unpractical for large distributed organizations

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Scenario

So, we are concerned in:

- continuous reauthentication
- using mouse dynamics
- collected w/o specific software installed on client machine

Scenario

We chose to address:

- web
- full transparency to server and client

Suitable for:

- large organizations w/ user web access
- (private) cloud hosted enterprise applications

Example

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Authentication, then reauthentication in the web using mouse dynamics. Aim at detecting long lasting systematic fraudulent account usage (*defense-in-depth*).

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Our contribution

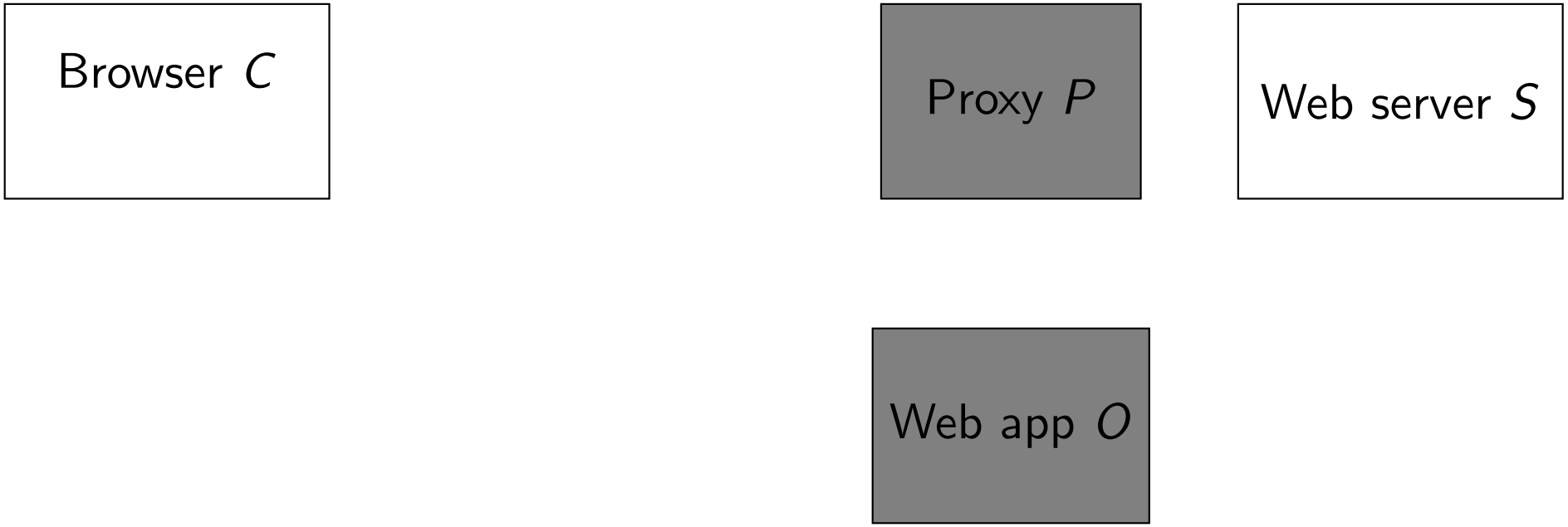
In a nutshell:

- a system for capturing web GUI-related events transparent for user and web site
- a procedure for performing continuous reauthentication using mouse-generated events

Data capture system: overview

- a web proxy
- a js (collects data)
- a web app (receives and analyzes data)

How it works



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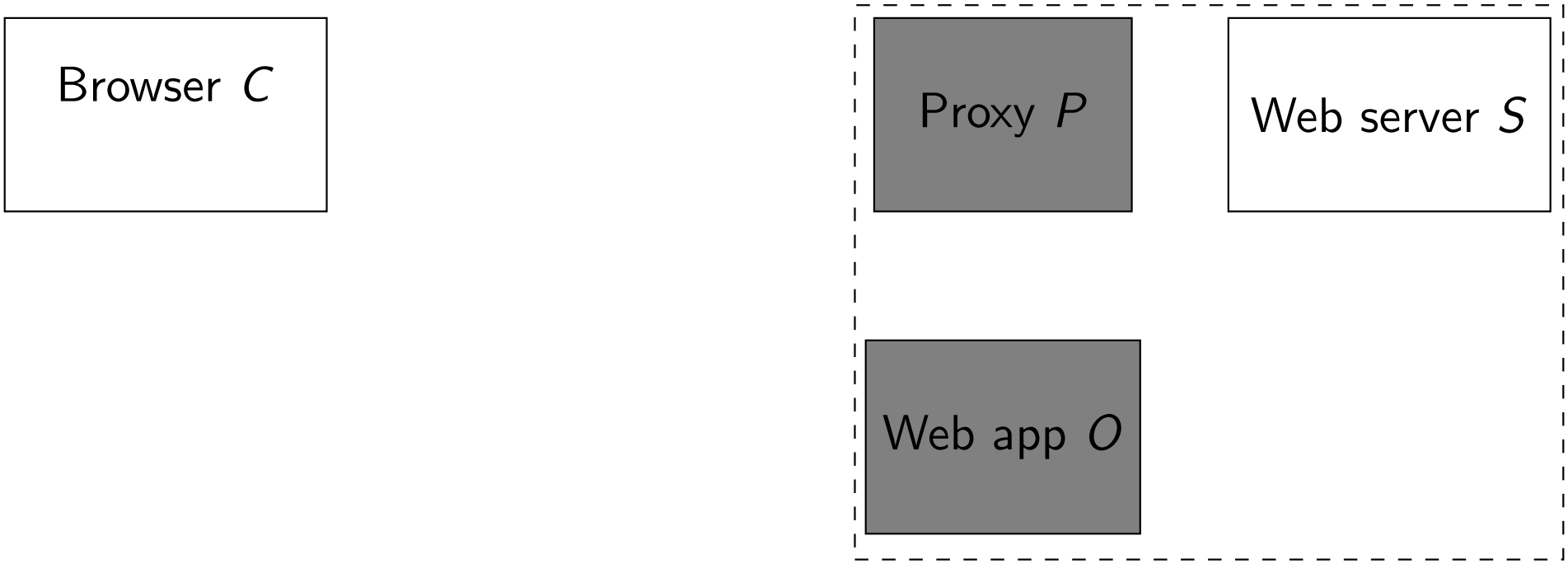

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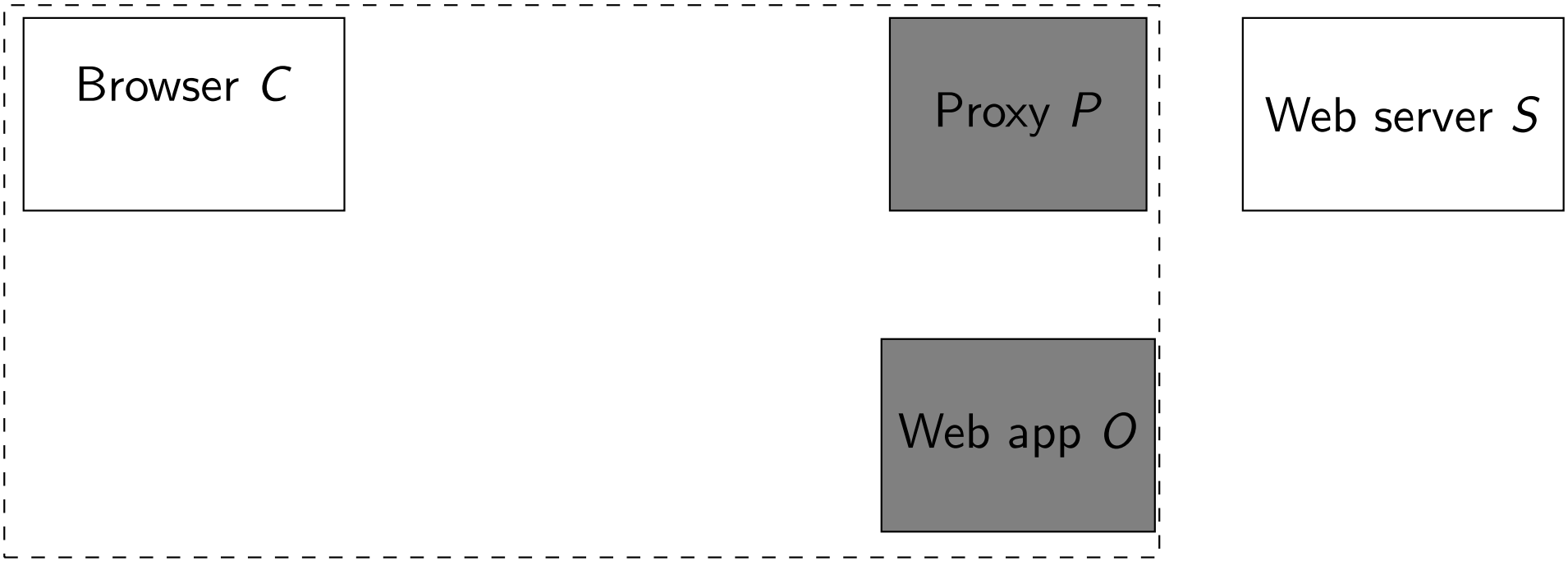

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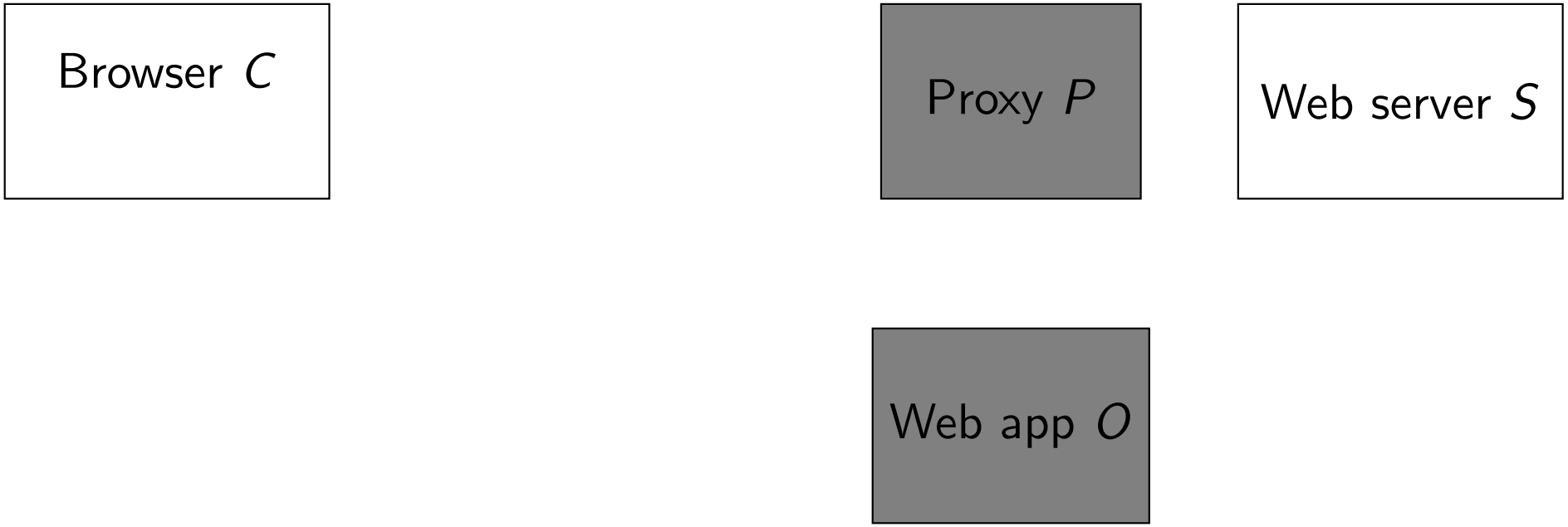

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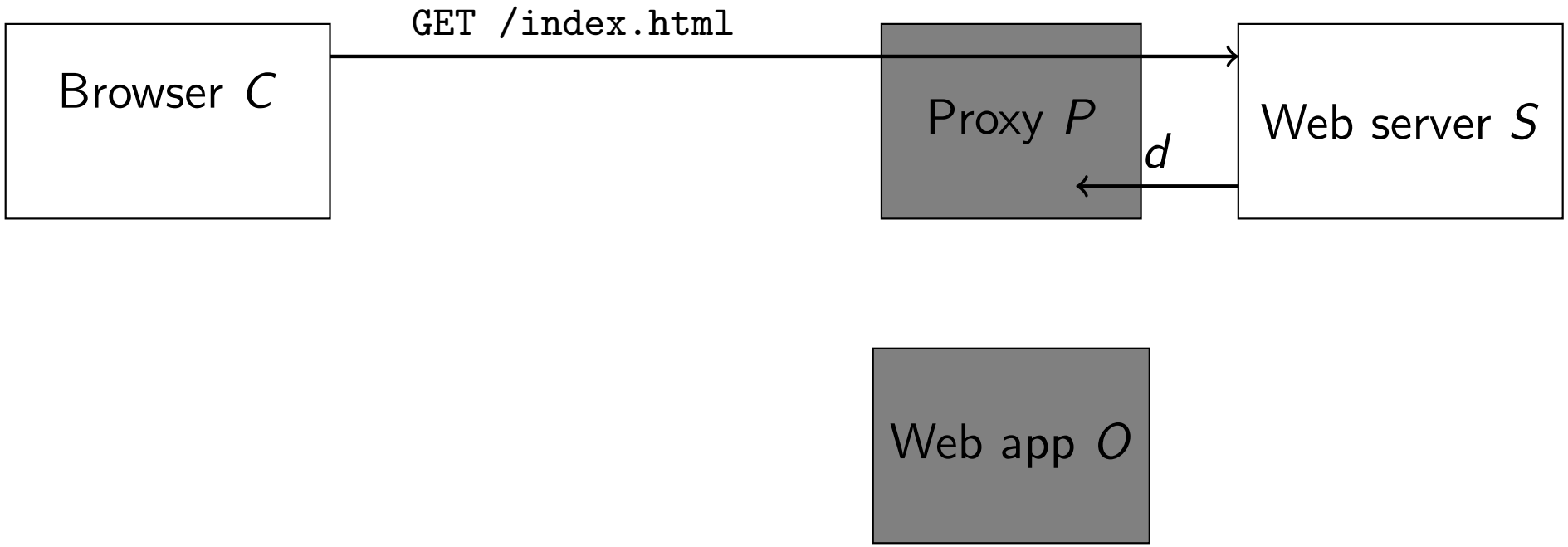

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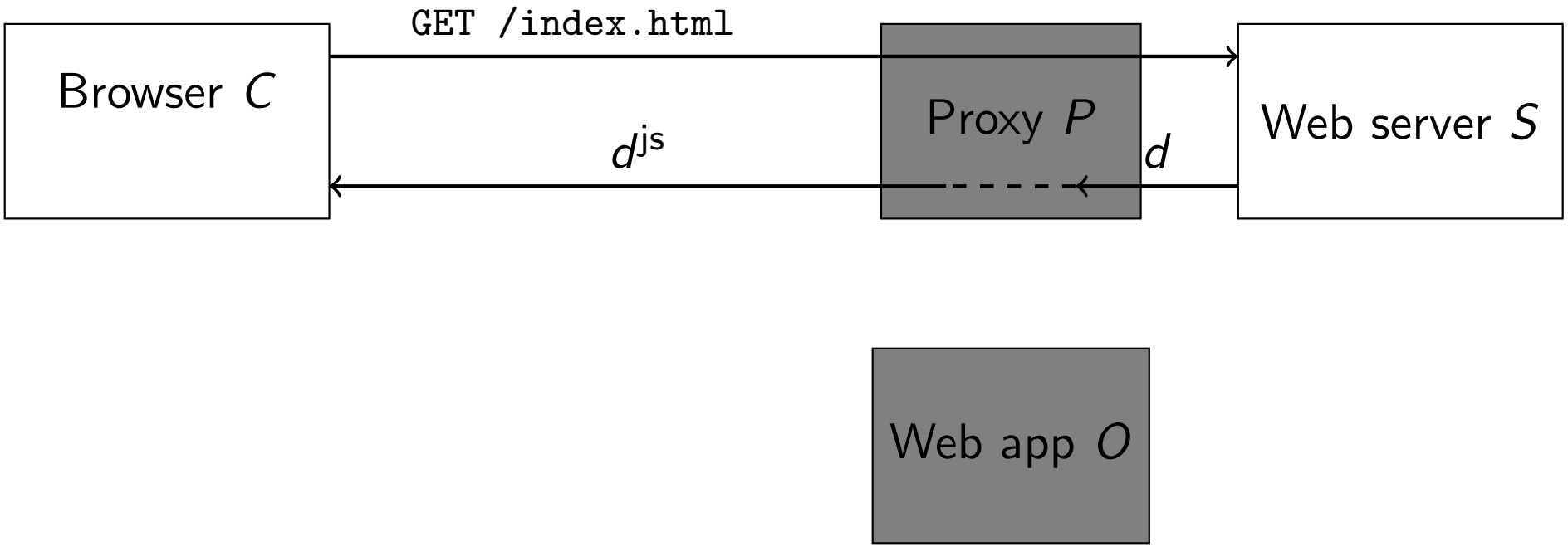

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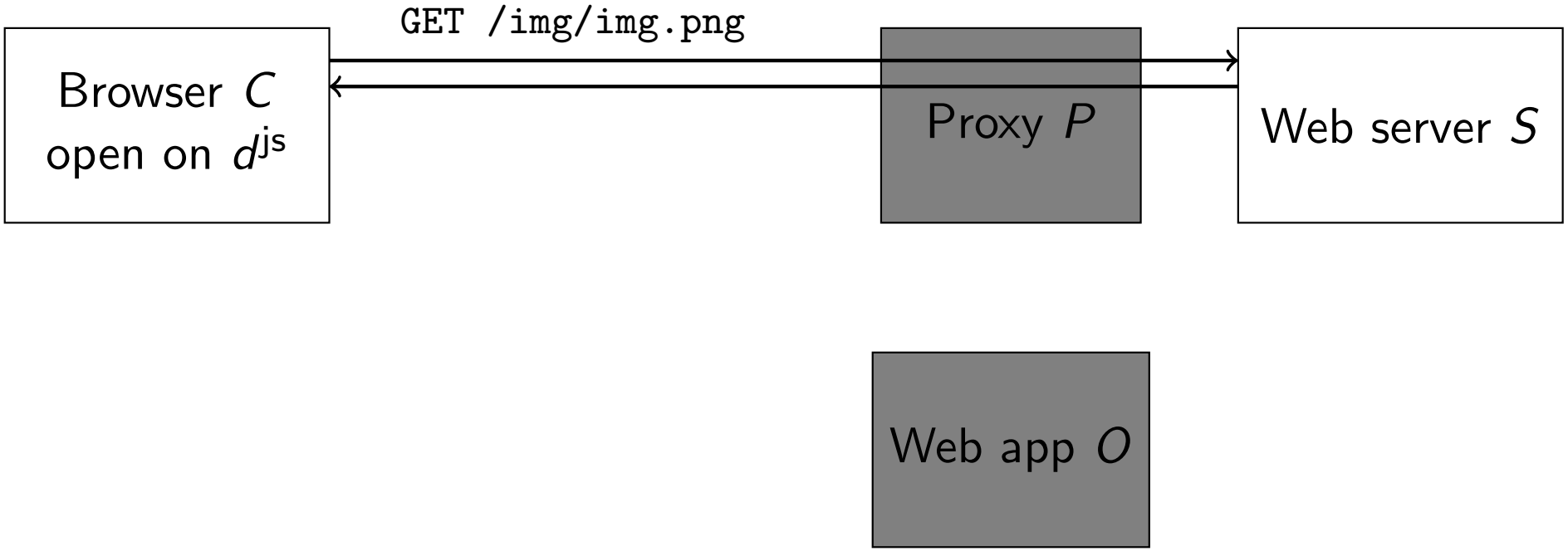

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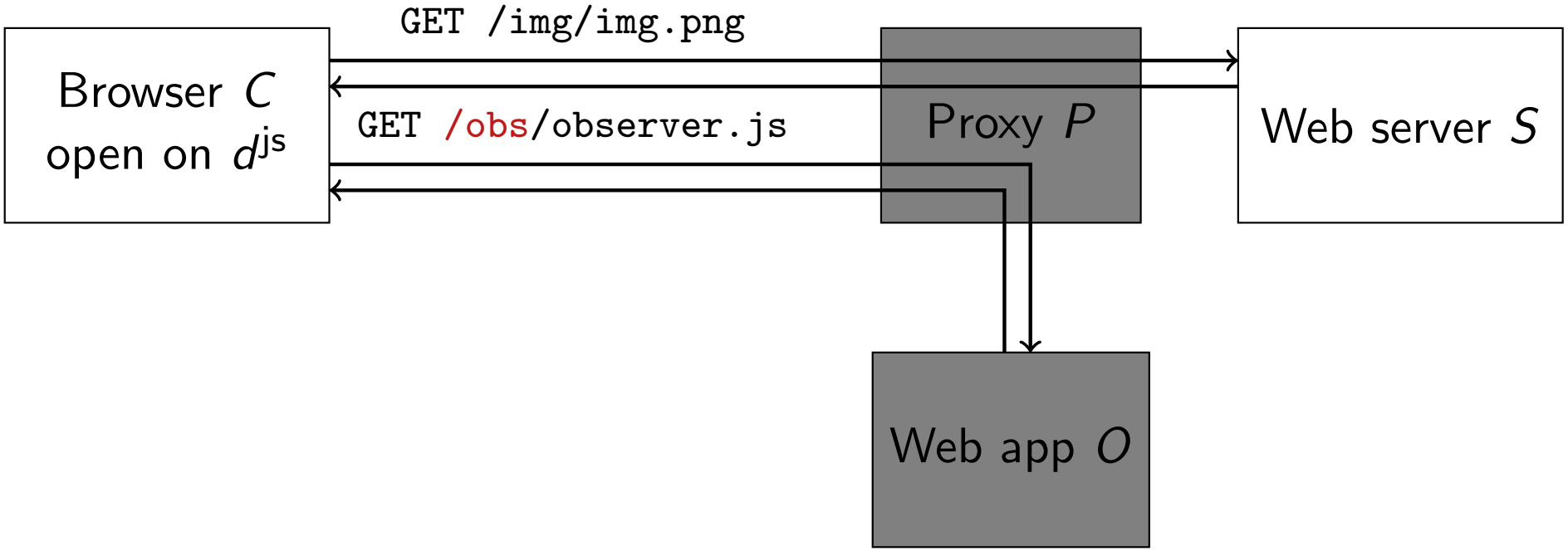

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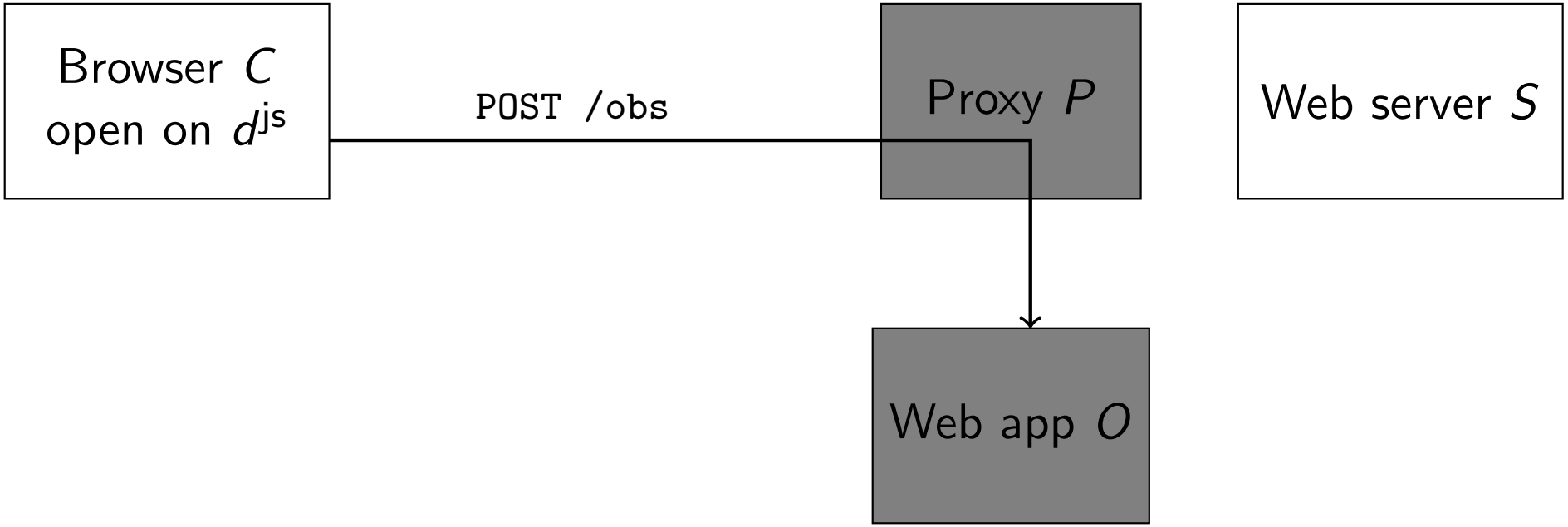

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4. our js on C sends mouse events data to `/obs`, i.e., O

Data capture system

- fully transparent to both user and web sites, requires only to set the proxy
- redirection of `/obs/*` traffic allows to circumvent Same Origin Policy
- low bandwidth usage ($\approx 2.5\,\mathrm{kB\,s^{-1}}$)
- can work with HTTPS (w/ self-signed certificate)

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- low bandwidth usage ($\approx 2.5\,\mathrm{kB\,s^{-1}}$)
- can work with HTTPS (w/ self-signed certificate)
- could be used also for other purposes: web app testing[1], web app misuse detection, ...

[1] Bartoli, Medvet, Mauri, *Recording and Replaying Navigations on AJAX Web Sites*, Int. Conf. on Web Engineering (ICWE), 2012

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Procedure: overview

Data capture system generates an event $e = (x, y, t)$ every $\approx 25\,\text{ms}$, then we:

1. split sequence of events on pauses $\geq 500\,\text{ms}$ and consider the last 10 events before a pause (*trajectory*)
2. transform a trajectory T into a vector $\mathbf{f}(T) \in \mathbb{R}^{39}$
3. classify $\mathbf{f}(T)$ as anomalous/normal, w.r.t. current authenticated user

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Features

$\mathbf{f}(T)$ includes:

- directions and direction changes
- speeds
- accelerations
- x- and y-extents

Classification

Two phases:

- training
- actual classification

Classification

Two phases: (U^- is the authenticated user)

- training based on trajectories of U^- and other users $U_1^+, U_2^+, \ldots$
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- training based on trajectories of U^- and other users $U_1^+, U_2^+, \ldots$
- actual classification based on trajectories of current unknown user U claiming to be U^-

Training phase

Once, at the beginning:

1. train a SVM_{U-} on the training set

Actual classification phase

For each T trajectory of U:

1. apply SVM_{U^-} to $\mathbf{f}(T)$
2. consider last w trajectories and...
3. ...if too many positives, raise an alert

Last w trajectories

Aggregation of several classifier outcomes:

- often used with mouse dynamics
- the higher w,
  - the higher the accuracy and
  - the longer the *Time to Detection* (TtD)

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Dataset

Two groups of users, each observed for several working days:

- 6 users, with different hardware equipment
- 18 users, with homogeneous hardware

Results

w	TtD (min)	Dataset 1 Acc.	Dataset 1 FAR	Dataset 1 FRR	Dataset 2 Acc.	Dataset 2 FAR	Dataset 2 FRR
50	13.5	83.3	16.6	16.7	76.4	21.8	25.4
100	27.1	88.5	12.8	10.2	81.4	17.5	19.6
200	54.1	93.5	9.2	3.8	86.6	13.5	13.3
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- accuracy up to 96%
- works better if attacker uses different hardware
- time to detection of tens of minutes

Time to detection

Time to detection of tens of minutes: is it practical?

- fits the threat model
- we can only monitor web usage (browser)
  - user could unfocus the browser for minutes
  - we consider sessions without pauses ≥ 10 minutes

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Thanks!