ReXCam: Resource-Efficient Cross-Camera Video Analytics at Scale

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Abstract

Enterprises are increasingly deploying large camera networks for video analytics. Many target applications entail a common problem template: searching for and tracking an object or activity of interest (e.g., a speeding vehicle, a break-in) through a large camera network in live video. Such cross-camera analytics is compute and data intensive, with cost growing with the number of cameras and time. To address this cost challenge, we present ReXCam, a new system for efficient cross-camera video analytics. ReXCam exploits spatial and temporal locality in the dynamics of real camera networks to guide its inference-time search for a query identity. In an offline profiling phase, ReXCam builds a cross-camera correlation model that encodes the locality observed in historical traffic patterns. At inference time, ReXCam applies this model to filter frames that are not spatially and temporally correlated with the query identity’s current position. In the cases of occasional missed detections, ReXCam performs a fast-replay search on recently filtered video frames, enabling graceful recovery. Together, these techniques allow ReXCam to reduce compute workload by 8.3× on an 8-camera dataset, and by 23× – 38× on a simulated 130-camera dataset. ReXCam has been implemented and deployed on a testbed of 5 AWS DeepLens cameras.

1 Introduction

The Internet of Things (IoT) has led to an explosion of data sources, and applications that rely on real-time inferences over these data. In parallel, the models making these inferences have improved in accuracy, even surpassing humans for certain vision tasks, but at increased resource cost. This work addresses the systems challenges of scaling up IoT applications to enable live video analytics on a fleet of cameras.

Live video analytics over a fleet of camera feeds embodies two key trends—massive data sources and compute-intensive inference (e.g., neural nets). On the one hand, enterprises deploy large camera networks for public safety and business intelligence [11]. For instance, Chicago and London police access footage from 30,000 and 12,000 cameras to respond to crimes in real time [4, 5]. On the other hand, many applications rely crucially on cross-camera video analytics, i.e., detecting, associating and tracking queried “identities” in the live streams as these identities move across the camera feeds over time (e.g., high-value shoppers in a store [8, 34] or suspects in a city [46, 66]). However, cross-camera analytics applications are computationally more challenging than “stateless” single-camera vision tasks (such as object detection in one camera feed) as they entail discovering associations across frames and across cameras. Their compute cost thus grows with the number of cameras.

Prior work falls short of addressing this challenge. Work in computer vision improves accuracy of cross-camera analytics (e.g., [55, 58, 70]), but it has largely ignored the prohibitive compute costs. Recent systems have accelerated analytics on live videos via frame sampling and/or cascaded filters for discarding frames [25, 28, 37, 40, 63, 65]. However, they share a key drawback that they optimize the execution of analytics on single video feeds, independent of the other streams. Thus, the compute cost of cross-camera analytics still grows with more deployed cameras and longer activity time.

Spatio-temporal correlations: Our main insight is that the cost of cross-camera analytics can be drastically reduced by exploiting the physical correlations of objects among the camera streams. We develop ReXCam, a cross-camera analytics system that leverages inherent spatio-temporal correlations to aggressively prune the set of camera streams to be processed, thus decreasing compute costs. In the ideal case, ReXCam reduces cost to the number of cameras that the queried object
appears in at any point in time and not the total number of deployed cameras. A key property of cross-camera applications is that objects of interest appear only in a small number of cameras at any time, even in large camera deployments.

Spatial correlations indicate geographical association between cameras – the probability that objects seen in a source camera will move next to a particular destination camera’s field of view. Temporal correlations indicate association between cameras over time – the probability that objects seen in a source camera will move next to a destination camera’s view at a particular time. These spatio-temporal correlations enable ReXCam to guide its cross-camera inference search toward cameras and frames most likely to contain the query identity (see Figure 1). ReXCam’s use of spatio-temporal correlations to cut the cost of cross-camera analytics is fundamentally different than the cross-camera correlations used by recent work (e.g., [37]) that optimizes the resource-accuracy profiling but not the live video analytics itself, which still executes on each stream independently.

Challenges: ReXCam, at its core, applies the physical properties in the IoT world (spatio-temporal correlations across cameras) to high-level AI applications (cross-camera video analytics). This has led to three main challenges. First, automatically obtaining spatio-temporal correlations is expensive on unlabeled video data. Second, applying spatio-temporal correlations to existing single-camera inference modules (e.g., object trackers) is non-trivial and requires clean abstractions with the necessary system supports. Finally, any spatio-temporal profile is bound to have errors that will lead to missing objects, which need to be detected and rectified efficiently.

To tackle these challenges, ReXCam operates in three distinct phases. 1) In an offline profiling phase, it constructs a cross-camera spatio-temporal correlation model from unlabeled video data, which encodes the locality observed in historical traffic patterns. This is an expensive one-time operation that requires detecting entities with an offline tracker, and then converting them into an aggregate profile of cross-camera correlations. 2) At inference time, ReXCam uses this spatio-temporal model to filter out cameras that are not correlated to the query identity’s current position (camera), and is thus unlikely to contain its next instance. 3) Occasionally, this filtering will cause ReXCam to miss query detections. In these cases, ReXCam performs a fast-replay search on recently filtered frames (that it stores), uncovers the missed query instances, and gracefully recovers into its live search.

Evaluation Highlights: We evaluate ReXCam using the well-studied DukeMTMC video data [55] from the Duke campus. On this 8-camera dataset, ReXCam saves compute cost by $8.3 \times$ over a correlation-agnostic baseline ($\sim 90\%$ of the ideal savings). These savings come at a drop in recall of only $1.6\%$. We also use a simulated dataset of 130 cameras in Porto (using GPS trajectories) [10], and report savings of $23 \times \sim 38 \times$. Interestingly, ReXCam improves precision by $39\%$, perhaps because the spatio-temporal pruning acts as a “low pass filter”.

Finally, we have implemented and deployed ReXCam on a small testbed of 5 AWS DeepLens smart cameras [13].

Contributions: Our work makes three main contributions.
1) We quantify the potential for harnessing spatio-temporal correlations in cross-camera video analytics.
2) We build a cross-camera video analytics system that learns and applies spatio-temporal profiles on live videos.
3) We develop robust error-handling mechanisms to avoid missed detections by storing and searching on recent videos.

2 Motivation and Background

We explain some example cross-camera video analytics applications (§2.1), the modules in their analytics pipelines (§2.2), and then the compute models for video analytics (§2.3).

2.1 Cross-camera analytics applications

Large camera networks are installed in cities (such as London, Beijing, and Chicago), transport facilities (traffic intersections, airports), and enterprise campuses (corporate offices, retail shops) [1,5,12,66]. A common class of applications in these camera deployments rely on re-identifying and following objects (e.g., people or vehicles) as they move across the views of the different cameras. The focus is on following select “objects of interest” that are typically provided by external entities (such as law enforcement). A key characteristic of cross-camera applications is that objects of interest occur only in a small fraction of the cameras at any given time.

1) Public safety. Cross-camera video analytics helps localize suspects after a security breach. For example, after a reported incident of a person pulling out a gun inside an office building, we will want to track that person (whose image can be obtained from the camera footage) across the cameras in the building while security personnel are dispatched.

Alternatively, after a major public attack (e.g., in a train), law enforcement may track the accomplices of the identified perpetrator, which may be obtained from police databases that store people frequently associated with the perpetrator [66]. Following these accomplices across the thousands of cameras in the city allows for effective police apprehension.

2) Vehicle tracking in traffic cameras. In the U.S. and Europe, AMBER alerts are raised on suspected child abductions [2]. The license plate and vehicle details are obtained from investigations, and alerts are broadcast to citizens in the area [2]. Tracking of the suspect’s vehicle across the thousands of cameras on highways and city streets can keep tabs on the suspect and victim, even as police intervene [46].

Likewise, when traffic police notice a vehicle speeding or making a dangerous maneuver, they will note its details and will be interested in tracking the vehicle as it moves across the city using cross-camera analytics to assess its behavior.

3) Retail store cameras. Using computer vision to improve shopping experience is a big thrust among retailers. “Special” shoppers (e.g., loyal customers, or customers on wheelchairs) are identified as they enter the store and cross-camera analyt-
ics can be used to track them across the hundreds of cameras in the store to make sure they are provided timely attention (e.g., dispatching a store representative) when necessary.

### 2.2 Video analytics pipelines

Video analytics pipelines for cross-camera applications (in §2.1) typically consist of a series of modules on the decoded frames of the video stream: (1) an object detection module, which extracts and classifies objects of interest in each video frame (e.g., people, gun), and (2) a re-identification module, which given a query image (e.g., of a person), returns positions of co-identical instances of the query in subsequent frames (if present). Cross-camera analytics pipelines detect objects in each camera, and track the objects across cameras. Core to this pipeline is the vision primitive of identity re-identification [39, 50, 56]. Given an image of a query identity \(q\), a re-identification (re-id) algorithm ranks every image in a gallery \(G\) based on its feature distance \(d\); the lower the distance the higher the similarity (Figure 2). Typically, features are the intermediate representation of a neural network trained to associate instances of co-identical entities.

Object detection and re-id are the most challenging steps of cross-camera video analytics – in terms of cost and accuracy – and our work focuses on improving both of them.

**Cost.** Tracking in large camera networks is computationally expensive. Tracking even a single object of interest through a camera network, after an initial detection, can potentially require analyzing every subsequent frame in every camera (without good heuristics for geographic localization).\(^1\)

**Accuracy.** Re-id is a non-trivial problem in computer vision [59, 68], being particularly difficult in crowded scenes and in large camera networks due to significant differences in lighting and viewpoint across cameras. Often, re-id models must rely on weak signals (like clothing), thus making it difficult among a large gallery of objects in a frame.

Our use of spatio-temporal correlations to prune the video frames to analyze – i.e., run object detection and re-id – significantly cuts down the inference space, thus improving both cost as well as accuracy. While our focus is on cross-camera applications, we also show how spatio-temporal correlations improve the cost of even single-camera applications (§5.4).

### 2.3 Setup and compute model

Consistent with existing deployments [23, 29, 47], our focus is on “edge” computation of video analytics. In our setup, all the cameras are in a high-speed local network with sufficient bandwidth to an edge compute box (e.g., Azure Data Box Edge [3]) that is managed by the enterprise (that has deployed the cameras). For example, cameras in an office building are analyzed in an edge box located in the same building. Traffic cameras in a city are analyzed in the local traffic command center [45]. Videos are streamed to this edge box and the pipeline modules (§2.2) including object detection and re-id are run on this edge. Reducing the compute load enables more video feeds to be processed on the edge box or alternately reduces the resources to be provisioned.

Our ideas also readily apply to a network of AI cameras (as we implement and deploy in §7), each of which consist of compute on-board, accelerators (e.g., GPUs), and storage [13, 53]. Our techniques will enable each camera to be provisioned with much lower resources, thus lowering their cost.

### 3 Quantifying spatio-temporal correlations

We analyze the potential of using spatio-temporal correlations for cross-camera video analytics using the DukeMTMC dataset [55]. We study cross-camera identity tracking that involves tracking an object of interest, in real time, through a camera network. In particular, given an instance of a query identity \(q\) (e.g., a person) flagged in camera \(c_q\) at frame \(f\), we return all subsequent frames, across all cameras, in which \(q\) appears as it moves around. We measure the reduction in compute, i.e., the number of frames on which object detection and re-id operations (§2.2) are executed.

#### 3.1 Empirical analysis on cross-camera correlations

We now present an empirical study to quantify the cross-camera correlations in the DukeMTMC dataset [55], one of the most popular benchmarks in computer vision person re-id and tracking [60, 67]. This quantification motivates our design of a video analytics system that leverages such correlations to improve the performance of cross-camera analytics. The DukeMTMC dataset contains footage from eight cameras placed close enough that people frequently appear in multiple cameras, as is typical in camera deployments. The dataset contains over 2,700 unique identities across 85 minutes of footage, recorded at 60 frames per second [55].

#### 3.1.1 Spatial correlation.

Cross-camera movement of individuals (or “traffic”) demonstrates a high degree of spatial correlation. Here, “traffic” between cameras \(A\) and \(B\) is defined as the set of unique individuals detected in camera \(A\) that are next detected in camera \(B\). (Note that a person that moves from \(A\) to \(B\) via camera \(C\) are

\(^1\)Optimizations using frame sampling in each camera stream [28, 40] are orthogonal to our idea of using spatio-temporal correlations across cameras, and we will quantify this aspect in our experiments in §8.2.
Camera 8 to cameras 2 and 5 even though these are physically proximate. Thus, learning these patterns in a data-driven fashion is a more robust approach (as we will quantify in §8.2). Data-driven learning also allows us to capture asymmetry in the traffic patterns between cameras, for e.g., over 50% of traffic from camera-7 move to camera-6 but less than 25% of traffic moves in the reverse direction from camera-6 to 7.

### 3.1.2 Temporal correlation.

Cross-camera traffic also demonstrates a high degree of temporal correlation. As Figure 5 shows, travel times of individuals between a particular source camera and a destination camera in the DukeMTMC dataset are highly correlated. This is explained by the fact that these are static cameras and thus their pairwise distances are also static. Thus, for a given pair of cameras, the travel times for people to leave the feed of one camera and appear in the other camera are likely to be clustered around a mean value. In the DukeMTMC dataset, the average travel time between all camera pairs is 44.2s, and the standard deviation is only 10.3s (or only 23% of the mean).

Exploiting temporal correlations, even on its own, has the potential to provide compute savings. Given the task of locating a given query identity $q$, first identified in camera $c_q$, in one of the $n - 1$ possible destination camera streams, we can simply search each of the $n - 1$ streams (ignoring spatial correlations) but only for the time window when the query identities are most likely to show up. We probabilistically set the time window to be when at least 98% of the objects appear. Such an approach has the potential to reduce our compute load by 7.5× compared to a naive approach that does not use such a (time) windowed search. This shows the considerable potential in leveraging the tight distribution of travel times of individuals between the views of the cameras.

### 3.2 Potential gains: spatial & temporal correlations

We now put together the gains due to spatial and temporal filtering combined over a baseline that searches all $n - 1$ cameras (for a maximum duration). We assume ideal knowledge about the spatial correlations between the cameras as well as the temporal characteristics of travel times of individuals between the views of the cameras. Using the same thresholds as in §3.1, our analysis shows a potential gain of 9.4× savings.
in the compute cost. This encouraging potential for savings, even for a 8-camera dataset, motivates us to both learn and
exploit the spatio-temporal correlations for cross-camera video
analytics. As we will show in §8, ReXCam achieves 8.3×
reduction in compute cost, which is ∼90% of the potential.
In addition, the filtering of frames to search also improves the
precision of the results from 51% for the baseline approach to
90% with ReXCam, with little drop in recall.

4 ReXCam Overview

Building upon the strong spatial/temporal correlations across
cameras seen in §3, we develop ReXCam, a resource-efficient
cross-camera analytics system that leverages the correlations
across cameras to reduce computing cost. As depicted in
Figure 6, ReXCam provides two core functions for cross-
camera video analytics applications.

The spatio-temporal model (§5.1) describes the spatial and
temporal correlation between cameras, and can be queried by
applications. At a high level, one can query the model with
two cameras, $c_s$ and $c_d$, and a time window, and it will return
how likely an object leaving $c_s$ will appear in $c_d$ (i.e., the
spatial correlation) and if it appears in $c_d$ how likely it will
appear within the time window (i.e., temporal correlation).

The forward and replay analysis (§5.2 and §5.3) perform
real-time inference on live videos (i.e., forward) as well as
inference on history video (i.e., replay). Both capabilities
operate jointly, and replay search is inherently needed for
spatio-temporal pruning: ignoring a camera due to weak spa-
tial/temporal correlation will inevitably introduce false neg-
atives that a baseline of searching all cameras would have
avoided, so ReXCam provides the abstraction of replay search
to allow faster-than-real time search over some history videos
(that were ignored) for error correction.

In §5.2 we demonstrate how cross-camera identity tracking
(tracking an identity across cameras over time from a known
starting point) is performed using spatio-temporal pruning.
We also show the generality of the functionalities of ReXCam
by applying spatio-temporal pruning for cross-camera identity
detection (finding a queried identity, e.g., a lost child, in a large
camera deployment) in §5.4 that is both an important single-
camera application as well as ties to the cross-camera identity
tracking by providing it the starting point for its tracking.

5 Spatio-temporal correlations in ReXCam

We now describe ReXCam’s solution for leveraging spatio-
temporal correlations in cross-camera video analytics.

5.1 Defining the spatio-temporal model

ReXCam builds upon the cross-camera correlations in §3.

1) Spatial correlations capture associations between camera
pairs arising from the movement of traffic (individuals) be-
tween the views of the camera streams. The degree of spatial
correlation $S$ between two cameras $c_s, c_d$ is quantified by the
ratio of: (a) the number of individuals leaving the source cam-
erea’s stream for the destination camera, $n(c_s, c_d)$, to (b) the
total number of entities leaving the source camera:

$$S(c_s, c_d) = \frac{n(c_s, c_d)}{\sum n(c_s, c_i)}$$

When a large fraction of individuals that leave $c_s$’s view are
seen next in a camera $c_i$, we say that $c_i$ is highly correlated
to camera $c_s$. Note that $S$ may be asymmetric (as seen in our
analysis in §3.1.1); camera $c_i$ may not be highly correlated
with camera $c_s$, even if the converse is true. In cross-camera
identity search, ReXCam exploits spatial correlations by pri-
oritizing cameras that are highly correlated to the last camera
where the queried identity $q$ was spotted (called query camera).

2) Temporal correlations capture associations between cam-
era pairs over time. If a large fraction of the traffic leaving
camera $c_s$ for camera $c_d$ arrives within durations $t_1$ and $t_2$,
then camera $c_d$ is said to be highly correlated in the time win-
dow $[t_1, t_2]$ to camera $c_s$. The degree of temporal correlation
$T$ between two cameras $c_s, c_d$ during a window $[t_1, t_2]$ is the
ratio of: (a) individuals reaching $c_d$ from $c_s$ within a duration
window $[t_1, t_2]$ to (b) total individuals reaching $c_d$ from $c_s$:

$$T(c_s, c_d, [t_1, t_2]) = \frac{n(c_s, c_d, [t_1, t_2])}{n(c_s, c_d)}$$

Indeed, cameras in real-world deployments have substantial
temporal correlation (§3.1.2). In cross-camera identity search,
ReXCam exploits temporal correlations by prioritizing the
time window $[t_1, t_2]$ in which a destination camera is most
correlated with the query camera.

Spatio-temporal model Given a source camera $c_s$, the
current frame index $f_{curr}$ (which serves as a timestamp), and a
destination camera $c_d$, our proposed spatio-temporal model $M$
outputs true if $c_d$ is both spatially and temporally correlated
with $c_s$ at $f_{curr}$, and false otherwise. In our description, the
frame index $f_{curr}$ serves the role of the timestamp.

The thresholds for being spatially correlated with $c_s$, and
temporally correlated with $c_d$ at time $f_{curr}$ are model par-
parameters. As an example, we may first wish to search cameras
receiving at least $s_{thresh} = 5\%$ of traffic from $c_s$, during the
time window containing the first $1 - t_{thresh} = 98\%$ of traffic
from $c_s$. These parameter settings exclude both outlier cam-
eras (cameras receiving less than 5% of the traffic from $c_s$)
and outlier frames (frames containing the last 2% of the traffic from $c_d$). Defining $s_{\text{thresh}}$ and $t_{\text{thresh}}$ as a percent of traffic (or individuals) directly translates to precision and recall of the entities being tracked. $M$ is formally defined as:

$$M(c_s, c_d, f_{\text{curr}}) = \begin{cases} 
1, & S(c_s, c_d) \geq s_{\text{thresh}} \\
\text{and} & T(c_s, c_d, f_{\text{curr}}) \leq 1 - t_{\text{thresh}} \\
0, & \text{otherwise}
\end{cases}$$

(1)

Here $f_0$ is the frame index at which the first historical arrival at $c_d$ from $c_s$ was recorded. The reason of having $f_0$ is because it takes time to travel from $c_s$ to $c_d$, and cost savings can be maximized by not searching on frames while objects are moving between cameras. As a result, our temporal filter checks if the volume of historical traffic that arrived at $c_d$ between $[f_0, f_{\text{curr}}]$ is less than $1 - t_{\text{thresh}}$ of the total traffic. This ensures that $f_{\text{curr}}$ falls in the “dense” part of the travel time distribution, where we are likely to find $q$. (Note that we must check that $f_{\text{curr}} \geq f_0$. When $f_{\text{curr}} < f_0, M$ is false.) Figure 7 shows an illustration for using $M$ with $f_0$ values for each destination camera. (We construct the model $M$ in §6.)

**Search hits and misses:** Leveraging the spatio-temporal model $M$ allows us to explore the subset of the inference space (camera streams and time windows) that is most likely to contain $q$. A “hit” reduces cost, as we avoid searching the entire space. On the (rare) misses, we go back and find $q$ in the past video frames over all the camera streams we had filtered out using $M$. In §5.3, we will explain how we handle misses and mitigate the delay it introduces. Maximizing the cost savings from hits and minimizing the miss-induced delays is a tradeoff controlled by the parameters $s_{\text{thresh}}$ and $t_{\text{thresh}}$.

**Algorithm 1 Tracking with the spatio-temporal model**

1: **input:** video feeds $\{V_c\}$ for camera $c$,
2: $\text{sp\_corr}(c_s, c_d) \rightarrow \{\text{true, false}\}$
3: $\text{tp\_corr}(c_s, c_d, f) \rightarrow \{\text{true, false}\}$
4: for query $(q, f_q, c_q) \in Q$ do
5: $q_{\text{feat}} = \text{features}(q) \triangleright \text{extract image features}$
6: $f_{\text{curr}} = f_q + 1 \triangleright \text{init current frame index}$
7: $M_q = [] \triangleright \text{init query match array}$
8: phase = 1 \triangleright \text{start phase one}
9: while $(f_{\text{curr}} - f_q) \leq \text{exit\_t}$ do
10: $V_{\text{corr}} = \text{filter}(\text{sp\_corr}, \text{tp\_corr}, c_q, f_{\text{curr}}, V)$
11: frames = get\_frames($V_{\text{corr}}, f_{\text{curr}}$)
12: gallery = extract\_entities(frames)
13: ranked = rank\_reid($q_{\text{feat}}, \text{gallery}$)
14: if ranked[0][dist] < match\_thresh then
15: $M_q = \text{append}(M_q, \text{ranked[0][img]})$
16: $q_{\text{feat}} = \text{update\_rep}(q_{\text{feat}}, \text{ranked[0][feat]})$
17: $f_q = f_{\text{curr}}$
18: phase = 1 \triangleright \text{reset to phase one break}$
19: $f_{\text{curr}} = \text{increment}(f_{\text{curr}})$
20: if phase = 1 and $T(c_s, c_d, [f_0, f_{\text{curr}}]) > 1 - t_{\text{thresh}}$ then
21: $f_{\text{curr}} = f_q + 1 \triangleright \text{reset frame index}$
22: $\text{sp\_corr} = \text{relax}(\text{sp\_corr})$
23: $\text{tp\_corr} = \text{relax}(\text{tp\_corr})$
24: phase = 2 \triangleright \text{start phase two}$
25: **output:** matched detections $\{M_q\}$

**5.2 Cross-camera identity tracking**

Algorithm 1 explains our cross-camera identity tracking. In cross-camera identity tracking, the input consists of a query image $q$, last seen in frame $f_q$ on camera $c_q$. (If the input does not contain the frame $f_q$, we can first run the next application, multi-camera identity detection, to locate it.) The goal is to flag all subsequent frames, on all cameras, where $q$ appears. Note that $q$ can appear again on the same camera ($c = c_q$), different cameras ($c \neq c_q$), or else exit the network altogether. For each query $q$, we begin by extracting image features $q_{\text{feat}}$ and initializing an empty array of discovered matches $M_q$. For each frame, as explained in §2.2, we: (1) extract individuals (objects) from each frame using an object detection model, (2) rank the objects based on their feature similarity distance to $q$ using a re-id model (Figure 2).

If the top-ranked detection is within a threshold (match\_thresh in Algorithm 1), i.e., a co-identical instance is found by the re-id model, we add the detection to our array of matches $M_q$, update our query representation $q_{\text{feat}}$ to incorporate the features of the new instance of $q$, update the query frame index $f_q$ to $f_{\text{curr}}$, and proceed with tracking $q$; lines 14-18. We continue searching until the gap between the last detected instance of $q$ and our current frame index exceeds a pre-defined exit threshold (defined as exit\_t in Algorithm 1). At this point, we conclude that $q$ must have exited the camera.
network, and cease tracking \( q \).

We apply the spatio-temporal model to cross-camera tracking as follows (marked in blue in Algorithm 1). The model \( M \) has two filters (lines 2 and 3): (1) \text{spatial\_corr}(c_s, c_d), which given a source camera \( c_s \) and a destination camera \( c_d \) returns true if \( c_d \) is correlated with \( c_s \), and (2) \text{temporal\_corr}(c_s, c_d, f), which given a source camera \( c_s \), a destination camera \( c_d \), and a frame index \( f \), returns true if \( c_d \) is correlated with \( c_s \) at \( f \). At query time, these two functions are passed to the \text{filter} function (line 10), which given a list of video feeds \( V \), returns the subset of cameras \( V_{\text{corr}} \) that are both spatially and temporally correlated to \( c_d \) at \( f_{\text{curr}} \).

Applying \text{filter} reduces the inference search space, at each frame step \( f_{\text{curr}} \), from all entity detections at \( f_{\text{curr}} \) on every camera to all entity detections at \( f_{\text{curr}} \) on \textit{correlated} cameras. This allows us to abstain from running object detection and feature extraction models on non-correlated cameras, and reduces the size of the re-id gallery in the ranking step. If \text{filter} in Algorithm 1 were applied to the example in Figure 7, the set \( V_{\text{corr}} \) would be only \( C_1 \) in in the times \([0, 10] \), only \( C_2 \) in the times \([10, 20] \), and null set at all other times.

5.3 Handling pruning errors via replay search

Spatio-temporal pruning may cause a drop in recall: missing actual occurrences of the query identity \( q \), which would be discovered by a baseline that exhaustively searches all the frames of all the cameras. When tracking on the spatially filtered cameras does not discover \( q \) after exit \( t \) time (line 22 in Algorithm 1), we will initiate a “second pass” through the video frames that we skipped; we call this \textit{replay search}.

\textbf{Replay subset:} We initiate replay search on a broader subset of cameras and timespans. In particular, we go back to the last camera that the queried identity was seen, \( c_q \) (i.e., restart the tracking procedure from \( f_{\text{curr}} = f_q + 1 \), line 23, as \( f_q \) was the last frame the queried object was seen), and find all the correlated cameras and time windows that \( c_q \) is correlated with using the spatio-temporal profile \textit{but} now with thresholds \( s_{\text{thresh}} \) and \( t_{\text{thresh}} \) decreased by a factor of 10. If we do discover an instance of \( q \), we proceed with tracking from that detection, initiating a new phase one in Algorithm 1. If we still do not, we search the entire camera network until the exit threshold.

Note that despite relaxing \( s_{\text{thresh}} \) and \( t_{\text{thresh}} \), the cameras over which we perform replay search will still be only a small fraction of the overall camera network and for only a small duration in the past. This is because a vast majority of cameras (in a large deployment) will have never seen traffic (individuals) from \( c_q \). Implicit to replay search is also the ability to store videos in the past. However, this only needs to be for the last few minutes (few 100 MBs even for HD videos).

\textbf{Replay delay:} Searching on videos from the past indicates that we are lagging behind tracking the identity. Thus, it is desirable to speed up the search process. ReXCam processes the historical videos at faster-than-real-time.

\textit{a) Skip frame mode} – Process the historical videos at lower frame rate (via frame sampling) and lower resolution (via frame downsizing) to increase processing rate but potentially lower accuracy. We use offline profiling \([63, 65]\) to decide the frame rates and resolution to limit the drop in accuracy.

\textit{b) Parallelism mode} – Process the historical videos by parallelizing them across other cameras or edge machines (depending on the setup; §2.3) that are idle. As explained above, the broader replay search is likely still only a small subset of all the videos, so spare resources will be available.

We implement both solutions and investigate their trade-offs on accuracy and delay in our evaluation (§8.3).

5.4 Multi-camera identity detection

While our focus thus far has been on cross-camera video analytics, spatio-temporal models can also be applied to reduce the cost of single-camera analytics, e.g., find a lost baby or lost car in a mall’s or city’s cameras. This involves running object detectors \textit{independently on each camera stream}, and is expensive for large camera deployments. In this section, we apply our cross-camera spatio-temporal model (§5.1) to such single-camera “identity detection”. Not only is it an application of wide relevance on its own, it also ties closely with cross-camera tracking (§5.2) to provide it the starting point of the query \( q \) (which we have been referring to as camera \( c_q \)).

Identity detection refers to finding a given identity \( q \) (e.g., an image of a lost baby or suspect) in many camera streams. The intuition why the spatio-temporal model helps is that if \( q \) is not found in camera \( C_1 \) and the spatio-temporal model indicates that most objects appearing in camera \( C_2 \) have recently appeared in \( C_1 \), then camera \( C_2 \) is unlikely to contain \( q \). In other words, the model allows to prune the cameras and time windows in which \( q \) is unlikely to be found based on when and where \( q \) was not found earlier. At any point of time, we maintain a probability for each camera to contain an object that has not been “scanned” (i.e., not found in the camera feeds we have searched so far). The cameras with high values of this probability will be prioritized in the search.

Formally, we define \( P_{c,w} \) to be the probability of any unscanned object \((i.e., an object that did not appear in any camera when it was searched) appearing in camera \( c \) in time window \( w \). Thus, the greater the \( P_{c,w} \) is, the more likely searching camera \( c \) in window \( w \) would yield a “hit”. We also define \( P_{c}^w \) is the probability of the identity entering the whole camera network at camera \( c \) at any point in time. We estimate this value by looking at the history trace and dividing the number of objects who appear camera \( c \) first by total number of objects. Then \( P_{c,0} = P_{c}^0 \) and \( P_{c,w} = P_{c}^w \) with \( w > 0 \) can be derived iteratively by the following equation:

\[
P_{c,w} = P_{c}^w + \sum_{w' \leq w} I_{c,w',w} \cdot P_{c,w',w'} \cdot S(c_t,c) \cdot T(c_t,c,w)
\]

where \( I_{c,w',w} \) is a binary flag indicating if camera \( c_{w'} \) was searched at time window \( w \) \((I_{c,w',w} = 0) \) or not \((I_{c,w',w} = 1) \). The equation can be intuitively interpreted as following: the probability of query object \( q \) to appear in camera \( c \) and time window...
At first glance, this will likely reduce the search accuracy as will track window \(w\) multi-vision. Before ReXCam is deployed, we first use a during the when there is a spike in pruning errors. Note that cameras the spatio-temporal correlations between the \(c_i\) initiate re-profiling. In particular, ReXCam tracks the num-

ers, they do happen, ReXCam can automatically detect them and cameras). These ‘changes are relatively infrequent, but when a busy segment, which can reduce the correlation between two

e.g., \(S(c_i, c)\) · \(T(c_i, c, w)\).

At any point in time, we search the camera \(c\) and time window \(w\) whose \(P_{c,w}\) is greater than a threshold \(\theta\). If the identity is found, the search ends. Otherwise, we set \(I_{c,wj} = 0\) and update other \(P_{c,w}\). This is run until we find the queried identity. §8.5 evaluates our gains with identity detection.

6 Profiling spatio-temporal correlations

A final piece of ReXCam system is the profiling and maintaining of the spatio-temporal correlations. ReXCam takes an approach that builds on standard techniques from computer vision. Before ReXCam is deployed, we first use a multi-target, multi-camera (MTMC) tracker to label entities in a dataset of historical video, collected from the same camera deployment on which the live tracking is executed. Logically, such a tracker will return for each detected entity instance \(i\) a tuple, \((c_i, f_i, e_i)\), containing the camera identifier \(c_i\), frame index \(f_i\), and entity identifier \(e_i\) for the detection, respectively.

Using these, we compute \(n(c_i, c_d, [t_1, t_2])\), the number of entities leaving any source camera \(c_i\) for any destination camera \(c_d\) within a time interval \([t_1, t_2]\). These quantities translate directly to our spatio-temporal model \(M\) in Eq. 1 (see §5.1).

However, directly using MTMC trackers to profile spatio-temporal correlations in the history video is computationally expensive, neutralizing the savings from the search pruning. This is because unlike single-target tracking, a MTMC tracker will track all entities in the dataset. To limit the profiling overheads, we explore the trade-off between the robustness of offline profiling and the accuracy of subsequent single-target cross-camera tracking using the generated model. In particular, the profiling cost can be reduced by labeling fewer frames with the MTMC tracker (e.g., by selecting a lower frame sampling rate or choosing a smaller subset of the data to label).

At first glance, this will likely reduce the search accuracy as the spatio-temporal correlations is based on a sampled subset of entities. In practice, however, we found that despite labeling fewer frames for the profiling, our precision and recall drops are only mild, and thus our solution of labeling fewer frames significantly reduces the profiling cost without impacting accuracy. We empirically show this in §8.4.

Finally, ReXCam needs to cope with potential changes in the spatio-temporal correlations (e.g., a road work may block a busy segment, which can reduce the correlation between two cameras). These ‘changes are relatively infrequent, but when they do happen, ReXCam can automatically detect them and initiate re-profiling. In particular, ReXCam tracks the number of objects that are missed in the normal pruned search but detected in the subsequent replay search (in an “uncorrelated” time interval or camera), and triggers a re-profiling of the spatio-temporal correlations between the corresponding cameras when there is a spike in pruning errors. Note that the error in the spatio-temporal profile during the re-profiling

Figure 8: ReXCam testbed deployment at AnonCampus with five AWS DeepLens smart cameras. The red lines show the walkways in the building, and we learn the spatio-temporal correlation of people traversing the walkways. The controller and all the cameras exchange “trigger” and “feedback” messages.

will not affect ReXCam’s inference, but only increase latency because the replay search handles the errors.

7 System Implementation & Deployment

We implement ReXCam with 1.5K line of Python code over AWS DeepLens smart cameras [13]. Each DeepLens camera runs Ubuntu OS-16.04 LTS, and is equipped with an Intel Gen9 GPU and Intel Atom Processor CPU, 8GB RAM, and 16GB built-in storage. Our testbed includes five such cameras connected to each other via Wi-Fi and deployed on Anon-Campus (Figure 8). In our testbed, video analytics modules (object detection, re-id) run on DeepLens’s on-chip GPU and CPU. The testbed of smart cameras contrasts the alternate model for video analytics using nearby edge boxes (§2.3).

We use a laptop (connected to the same Wi-Fi network as the cameras) to run the ReXCam controller. The ReXCam controller is responsible for profiling (§6) and maintaining the spatio-temporal model of correlations among cameras. The connectivity between the controller and the cameras is only to exchange “control messages” and not video data. We implement two main control inferences (Figure 8):

1. A trigger message from the controller to a camera triggers the camera to start (or stop) searching for a specified query identity in its video within a specified time interval. The trigger message can also be used to initiate search in history videos for replay search (§5.3).

2. A feedback message from a camera to the controller notifies the controller on an interesting incident (e.g., the specified identity has just been detected, or left the camera’s view) in real-time. A feedback follows an activation message and is sent as soon as the incident occurs.

Fault tolerance: The cameras broadcast a heartbeat every few seconds to the controller to handle instances of cameras failing. The ReXCam controller can be replicated for resilience. The only persistent state held by the ReXCam controller is the model of spatio-temporal correlations, which is backed up, and is updated only at coarse timescales. The spatio-temporal
130 cameras at intersections of the city (we get the cameras’
AnonCampus dataset
Porto dataset
is generated from 1,710,671 trajectories ob-
(four each) from the AnonCampus and DukeMTMC datasets.
1080p video from each camera recorded at 60 frames per sec-
video recorded at 24 frames per second, captured by five
8.1 Methodology
Our evaluation of ReXCam shows the following highlights.
1) ReXCam’s compute savings on the 8-camera
DukeMTMC dataset is 8.3 × (which is ∼90% of the poten-
tial; §3). ReXCam also improves precision from 51% to 90%.
On the larger simulated dataset of 130 cameras from Porto,
our savings grow with the number of cameras. (§8.2, §8.3)
2) Deployment on the 5-camera testbed with AWS
DeepLens cameras leads to 3.4 × savings in compute. (§8.2)
3) ReXCam’s optimizes to keep the profiling costs small
without impacting the precision and recall. (§8.4)

We evaluate ReXCam for single-camera analytics in §8.5.

8 Evaluation

8.1 Methodology
A. Datasets — We evaluate ReXCam on three datasets.
1) AnonCampus dataset (§7) consists of 35 minutes of 1080p
video recorded at 24 frames per second, captured by five
DeepLens cameras deployed in a school building (see Figure
8). The dataset is manually labeled with person identities.
2) DukeMTMC dataset is a video surveillance dataset with
footage from eight cameras installed on the Duke University
 campus (see Figure 3). The data consists of 85 minutes of
1080p video from each camera recorded at 60 frames per sec-
ond. In all, the footage contains over 2,700 unique identities
and over 4 million person detections (all labeled).

Figure 9 shows snapshots from eight different cameras
(four each) from the AnonCampus and DukeMTMC datasets.
3) Porto dataset is generated from 1,710,671 trajectories ob-
tained from 442 taxis running in the city of Porto, Portugal
between Jan. 2013 and June 2014 [10]. Each trajectory con-
tains timestamps and GPS coordinates sampled every 15 sec-
onds. To emulate cross-camera tracking, we manually pin
130 cameras at intersections of the city (we get the cameras’
coordinates from Google Maps) and set each camera’s field-
of-view to be a square area centered at the camera with length
l = 100m. We assume the accuracy of object detection and
re-id equal to the values reported in DukeMTMC-reID [7] for
objects in the camera’s view. The main objective is to measure
ReXCam’s gains in a large city-wide setting of cameras.
B. Models — For our re-id model, we use an open-
source, ResNet-50-based implementation of person re-id [6],
trained in PyTorch on a subset of the Duke dataset called
DukeMTMC-reID [7]. We then implement our tracking (Al-
gorithms 1), which applies this model iteratively at inference
time to discover all instances of a query identity in the Duke
dataset. Since DeepLens uses the cDNN and Intel GPUs, we
leverage person-reidentification-retail-0076 from the Open-
VINO model zoo [32] for re-id in the AnonCampus dataset.

To build our spatio-temporal model on unlabeled video
data (simulating real deployment conditions), we apply an
offline multi-target multi-camera (MTMC) tracker [9] (§6)
to label every person detection in a subset of the dataset (i.e.,
profile set with 16352 frames). We implement a profiler to
extract spatial and temporal correlations from these labels.

C. Workload — We run a set of 100 tracking queries, {q_i},
drawn from the test query partition of the DukeMTMC-reID
dataset [7] (20 from the AnonCampus dataset, and 100 from
the Porto dataset). Each tracking query consists of multiple
iterations. Each iteration involves searching for the next in-
stance, q_i’, of the query identity in the dataset, starting with
the initial instance q_0. A tracking query terminates when no more
instances can be found. Experiments on the DukeMTMC
dataset were conducted on AWS EC2 p2.xlarge instances
(contains one Nvidia Tesla K80 GPU).

D. Metrics — We report the following four metrics which
are computed over the entire query set. (i) Compute cost —
Number of video frames processed, aggregated over all queries {q_i}. (ii) Recall (%) — Ratio of query instances re-
trieved to all query instances in dataset, q_i’. (iii) Precision (%) —
Ratio of query instances retrieved to all retrieved instances,
r_i’. (iv) Delay (sec.) — Lag between position of tracker and
current video frame, in seconds, at the end of a tracking query.
This will be 0 for a query if no replay search was performed.
Compute cost, recall, and precision are reported in aggrega-
tion. Delay is reported as an average value per query.

E. Compared Schemes — To evaluate our spatio-
temporal filtering, we compare against two schemes:
1) Baseline (all) - Searches for query identity q in all the
cameras at every frame step. Uses state-of-the-art re-id model
[6], no spatio-temporal filtering is utilized.
2) Baseline (GP) - Searches for query identity q only in the
cameras that are in geographical proximity to the query cam-
era at every frame step. Uses state-of-the-art re-id model [6].
For DukeMTMC dataset, we manually set pairs of neighbor-
ing cameras using Figure 3 while for Porto dataset, we set
geographical proximity threshold to 4l (where l = 100m).
3) ReXCam - Searches for query identity q only on cameras
that are currently spatio-temporally correlated with c_q (as per
Algorithm 1). The same person re-id model is used as in the
baseline [6]. We consider various versions of Equation 1, cor-
responding to different spatio-temporal filters. Each version
is coded as Ss-Tr, where s indicates the spatial filtering thresh-
old and t indicates the temporal filtering threshold. Higher
values of s and t indicate more aggressive filtering (no t value
indicates no temporal filtering and helps measure the gains
of spatial filtering alone). For instance, S5-T2 filters cameras

Figure 9: Example snapshots from AnonCampus (left) and
DukeMTMC [55] (right) cameras.
that receive <5% of the traffic from query camera $c_q$. In addition, its filter frames outside the time window containing the first 98% of traffic from $c_q$.

## 8.2 Spatio-temporal filtering gains

Figure 10, Figure 11 and Figure 12 compare the performance of the baseline and various ReXCam versions on three datasets, respectively. We find that ReXCam significantly outperforms both baselines, by (1) reducing compute cost and (2) improving precision, while maintaining comparable recall. It is noteworthy that the best thresholds for ReXCam are dependent on the dataset. ReXCam versions S30-T1, S5-T2, S1-T1 offer the best trade-off between compute cost, recall, precision, and delay in the three datasets, and in general have to be tuned. We term these schemes ReXCam-O (optimal).

1) **Compute cost** – Baseline (all) is by far the most compute-intensive, processing 98,760 frames for 20 queries and 45,638/85,890 frames for 100 queries on the DukeMTMC/Porto dataset, respectively. Baseline (GP) saves the cost quite a bit but its performance fluctuates on different settings due to the discrepancy between spatial correlation and geographical proximity (as also pointed out in §3.1.1). Each successive version of ReXCam achieves lower compute cost than its predecessor. For instance, in Figure 11, the most aggressive version of ReXCam, S10-T10, processes only 3,513 frames, and achieves $13 \times$ lower compute cost on 8 cameras than the all-camera baseline. Similarly, a maximal value of $3.6 \times$ compute savings can be achieved in Figure 10.

In comparison, ReXCam-O processes 28,680/5,500/3,776 frames, which translates to $3.4 \times/8.3 \times/23 \times$ lower cost than the all-camera baseline in the five-camera (AnonCampus), eight-camera (DukeMTMC), and 130-camera (Porto) dataset.

2) **Recall (%)** – Compared with both baselines, recall of the ReXCam versions declines slightly when spatial/temporal filtering is introduced. In Figure 11, for example, baseline (all) achieves recall of 81.3%. Both spatial-only schemes achieve 79.3% recall. ReXCam-O achieves 79.7%, a 1.6% drop from the baseline. Similar patterns are observed in Figure 10 and Figure 12. The reason why recall becomes lower in the AnonCampus deployment is because of the increased instances of occlusions in indoor environments (see Figure 9). Note that in Figure 12, recall drops significantly from baseline (all) to baseline (GP), as a number of relevant cameras are mistakenly excluded by geographical proximity-based pruning.

3) **Precision (%)** – Baseline (all) achieves precision of 50.4%, 51.1% and 49.6% on three datasets, respectively. All versions of ReXCam improve on this, but ReXCam-O in particular achieves $71.7\%/90.4\%/85.8\%$ precision, which is a gain of $21.3\%/39.3\%/36.2\%$ over the baseline. Compared with baseline (GP), precision gain from ReXCam-O remains as high as $33.5\%/15.6\%$ on the DukeMTMC and Porto dataset. Higher precision is a key benefit of spatio-temporal filtering for cross-camera video analytics. By searching fewer irrelevant cameras, and fewer irrelevant frames, ReXCam is less likely to declare matches that do not actually match the query.

4) **Delay (sec.)** – Here we report total cumulative lag (lag in the absence of replay search (§5.3)), averaged over all queries. We do not report the delay from the AnonCampus deployment since among all 20 queries, only one needed replay search. For both DukeMTMC and Porto results, we find that delay increases with more spatial or temporal pruning. This is expected as there are more instances of misses. ReXCam-O, in
particular, incurs moderate delay – less delay than S5-T1 and S5-T10 but more delay than spatial-only filtering.

Given this analysis, ReXCam-O offers a favorable trade-off between the four metrics – achieving nearly the lowest compute cost ($3.4 \times 8.3 / 23 \times$ lower), nearly the highest precision ($21.3\% / 39.3\% / 36.2\%$ higher), competitive recall ($2.2\% / 1.6\% / 6.5\%$ lower), and moderate lag ($\approx 3.2s$), when compared to the locality-agnostic, all-camera baseline. Next, we analyze the impact of two key factors on ReXCam.

**Large-scale camera data:** The key objective of using the trajectories from the Porto dataset was to experiment on ReXCam’s gains at scale (§8.1); unfortunately there are no video datasets available for hundreds of cameras. Figure 13 shows cost savings and precision of ReXCam/Baseline (all) with increasing number of cameras. Cost savings steadily grows with increasing number of cameras, achieving up to $38 \times$ lower cost than baseline (all) in ReXCam S12-T12 for 130 cameras. We believe this is an encouraging result for ReXCam’s value for large camera deployments. All through, ReXCam maintains a 34.5% gain on precision with little impact on recall.

**Frame skipping:** Frame sampling is a key technique in prior work [28, 37, 65] to make single-camera analytics cheaper. Such techniques are orthogonal to ReXCam’s spatio-temporal pruning for cross-camera analytics, and we quantify our point. Figure 14 measures the impact of frame skipping—uniformly skip one in 3 frames, and one in 4 frames—on both baseline (all) and ReXCam. As shown in the figure, ReXCam maintains a much lower compute cost in both skipping cases. Specifically, the cost savings are $8.6 \times$ and $8.4 \times$, which is in the same ballpark as without frame skipping of $8.3 \times$, thus showing the orthogonality of frame skipping to ReXCam.

8.3 **Replay search**

In this section, we evaluate the effectiveness in reducing lag in replay search using the two proposed schemes from §5.3: **Skip frame mode** - Employ a $\times \frac{1}{3}$ frame sampling rate to increase throughput on historical frames, at the price of lower accuracy (via missed detections). ($\times \frac{1}{2}$ skip)

**Parallelism mode** - Employ a $\times$ 2 frame processing rate to increase throughput, at the price of increased compute cost (via increased resource usage). ($\times \frac{1}{2}$ ff)

Both schemes are applied to ReXCam-O, and compared to (a) the all-camera baseline and (b) ReXCam-O with the default real-time replay search, which incurs 2.6s of delay.

As Figure 15 shows, both $\times \frac{1}{2}$ skip and $\times \frac{1}{2}$ ff achieve delay reductions, decreasing final cumulative lag to 1.8s and 1.3s, respectively. The reason why $\times \frac{1}{2}$ skip doesn’t halve the delay is due to the skipped query instances during the first round of replay search where $s_{\text{thresh}}$ and $t_{\text{thresh}}$ decreased by a factor of 10. Also, delay reductions from $\times \frac{1}{2}$ skip and $\times \frac{1}{2}$ ff come with different tradeoffs, $\times \frac{1}{2}$ skip reduces delay by 1.2% to 78.0%, but increases precision from 90.37% to 90.87% and increase compute cost savings from 8.30× to 8.68× better than the baseline (by processing fewer historical frames). $\times \frac{1}{2}$ ff does not impact recall and precision, but reduces compute cost savings from 8.30× to only 8.27× better than the baseline.

8.4 **Profiling cost vs. tracking accuracy**

Profiling cost increases with the number of frames that must be processed by the MTMC tracker (§6). We investigate the trade-off between profiling cost and subsequent tracking accuracy. Specifically, we test whether we can build a precise spatio-temporal model on smaller subsets of the training data obtained by uniformly sampling the frames. We apply a sampling rate of $8 \times, 6 \times, 4 \times, 2 \times, \text{ and } 1 \times$ (using $X$ in 8 frames) in the profile partition of the Duke dataset (§8.1) for profiling, which translates to correspondingly lower profiling costs.

As Figure 16 shows, recall of ReXCam during live tracking reaches the maximum of 80.1% with 6× sampling, i.e., when half of the frames are labeled for offline profiling to
obtain the spatio-temporal model. Interestingly, on either side of this, the recall falls. On the left side, the drop is caused by insufficient amount of profiling data. On the right side, the small drop is because extra data results in a spatial-temporal model being overfit to the profile partition. This experiment indicates that spatial-temporal model can be built on a reasonably small set of training data (i.e., 37.1 min). However, the exact amount of data to train the spatial-temporal model varies among datasets, and thus should be chosen carefully. Precision remains stable (~90%) in Figure 16 when more than 4K (i.e., 2× sampling) frames are used for training.

If we combine the profiling cost with the cost of the live video analytics, we see that ReXCam would need to run only 34 live tracking queries to break-even with locality-agnostic tracking (calculations omitted). This represents a small fraction of the expected annual workload in large video analytics operations [65, 66] that track many hundreds of thousands of queries. Hence ReXCam’s profiling costs are small and will not dent the gains, leaving it to remain sizable.

8.5 Identity detection

Lastly, we evaluate ReXCam’s spatio-temporal pruning on identity detection, the single-camera application described in §5.4. As Figure 17 shows, ReXCam achieves as high as 7.6× cost reduction with θ = 0.95 on the 8-camera DukeMTMC dataset (θ is the likelihood threshold for searching a camera’s stream). Similar to trends in cross-camera tracking, the gain on precision far outweighs the drop on recall. In fact, for θ = 0.75, recall does not drop at all while precision improves by 28% even as cost savings stay at 6.6×. This experiment shows the generality of applying ReXCam for both cross-camera as well as single-camera applications.

9 Related Work

Video Analytics Systems. A sizable body of work on video analytics has emerged recently [28, 40, 46, 65]. Chameleon exploits correlations in camera content (e.g., velocity of objects) to amortize profiling costs, but not the cost of the video analytics itself [37]. These works leave three problems unexplored, each of which ReXCam addresses. First, they focus on single-frame tasks (e.g., object detection and classification), which are stateless. In contrast, surveillance applications, like the real-time tracking we focus on, involve multi-frame track-
10 Conclusions

Cross-camera analytics is a computationally expensive functionality that underpins a range of real-world video analytics applications, from suspect tracking to intelligent retail stores. We presented ReXCam, a system that leverages a learned model of cross-camera correlations to drastically reduce the size of the inference time search space, thus reducing the cost of cross-camera video analytics. ReXCam directs its search towards the camera streams that likely contain the identity being tracked, while gracefully recovering from (rare) misses using a replay search on historical videos. Our results are promising: ReXCam reduces compute workload by 8.3× on the 8-camera DukeMTMC dataset, and improve inference precision by 39%. On a simulated dataset of 130 cameras, its gains grow with the number of cameras. We have deployed a five camera testbed on campus, which we plan to expand for further experiments.

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