Cross-Camera Video Analytics in Large Enterprise Camera Deployments

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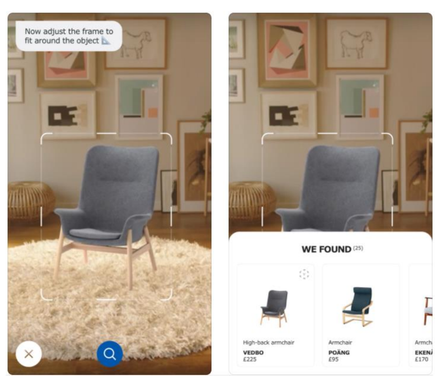
Introduction

Two trends in video analytics are triggering an increase in size and prevalence of enterprise camera deployments (both commercial and government):

1) **Falling camera costs** – an HDTV-quality camera with on-board SD card storage costs $20 today, down from $1,500 about three years ago.

2) **Advances in computer vision** – using neural nets (NN), can now: scan passenger identities via facial recognition (KLM's biometric passports), take a photo of a furniture item and search for it in an online catalog (IKEA's Place AR app), and convert a 2D video into a live 3D visualization in a AR device (UW and Facebook's 'Soccer on Your Tabletop').

KLM's biometric passport



IKEA's visual search app

UW's Soccer On Your Tabletop

Impact of larger camera deployments:

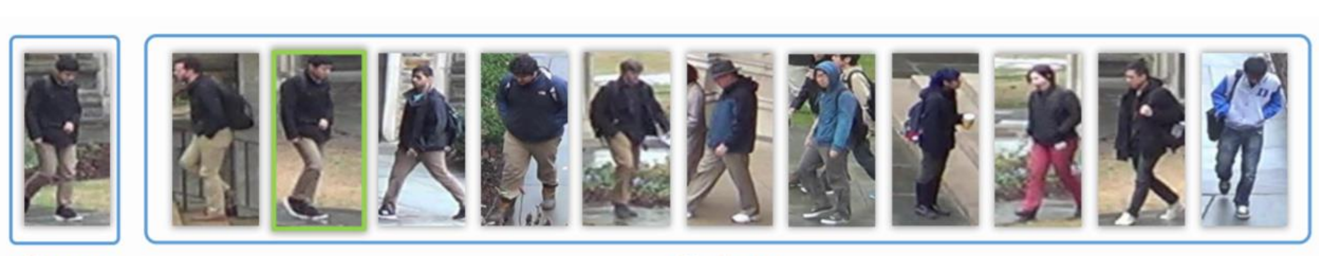
1) **Proportional increase in compute requirements** – as deployments scale, increased pressure placed on edge clusters, requiring greater resource provisioning (e.g. expensive GPUs), compute time, and human attention.

2) **Contention for human attention** – as deployments scale, human attention becomes the scarce resource. Central question: can we add more cameras, to cover larger areas, without requiring more human operators?

Multi-camera tracking

Problem template: track a person P through a camera network, in forward direction ("real-time tracking") or backward direction ("investigative search"), returning frames F in which person P is found. Track until P exits the network.

Multi-camera person tracking is built on a computer vision primitive known as person *re-id*entification. Re-id involves computing features on a query image **q** and each image $\{\mathbf{g_i}\}$ in a gallery, and ranking each $\mathbf{g_i}$ by its *feature distance* to **q**.



Given a query image q, rank images in a 'gallery' based on their similarity to q

Dataset

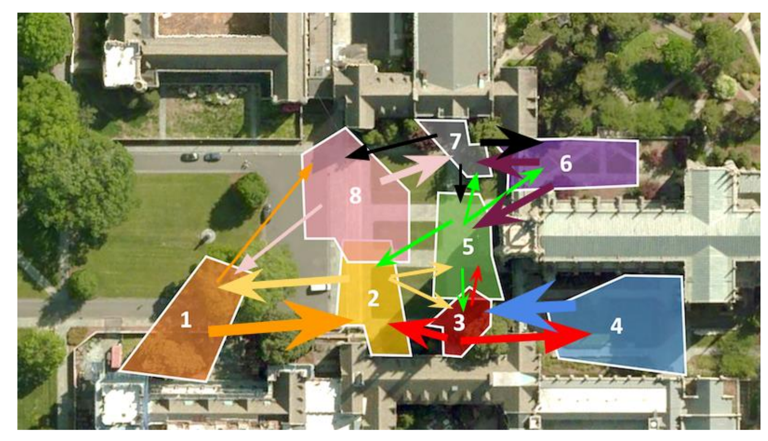
DukeMTMC dataset – footage from eight cameras installed on Duke U. campus

Opportunities

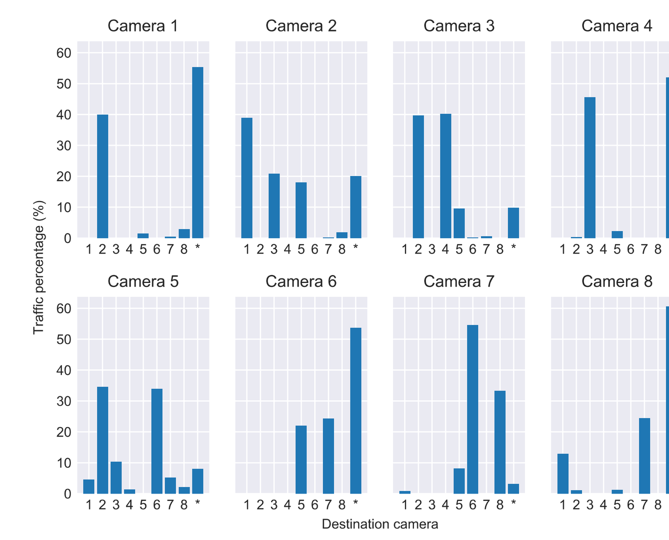
We leverage **spatio-temporal correlations** in large camera deployments to:

1) **Reduce resource cost** – by localizing a target object or person to a small group of cameras, can eliminate possibility of appearance in most other cameras in near-future. This in turn means that expensive, deep NN models can be turned off (or e.g. run at lower frame rates) on those video feeds.

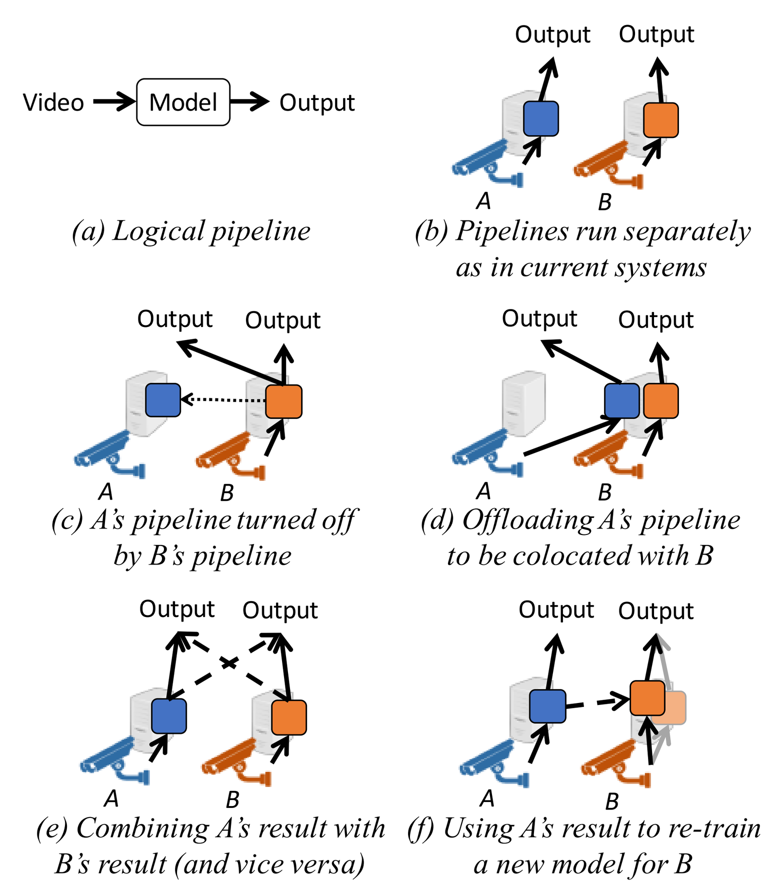
2) **Improve inference accuracy** – by pruning the search space, can reduce the probability of matching against incorrect detections (false positives), which dislodge subsequent tracking. Experiments confirm that this is a real and significant effect in tracking scenarios (see results).



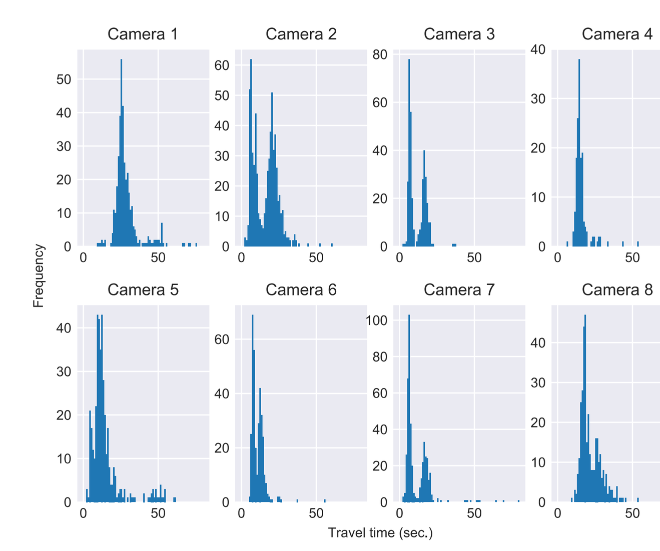
Duke dataset traffic visualization



Spatial traffic patterns (Duke)



Cross-camera pipeline opportunities



Temporal traffic patterns (Duke)

As the plots above indicate, foot traffic in the Duke dataset demonstrates significant spatio-temporal localization. Most traffic *leaving* a camera appears in only 2-3 other cameras (top). Travel times tend to fall in a narrow window that varies across cameras (bottom).

Results

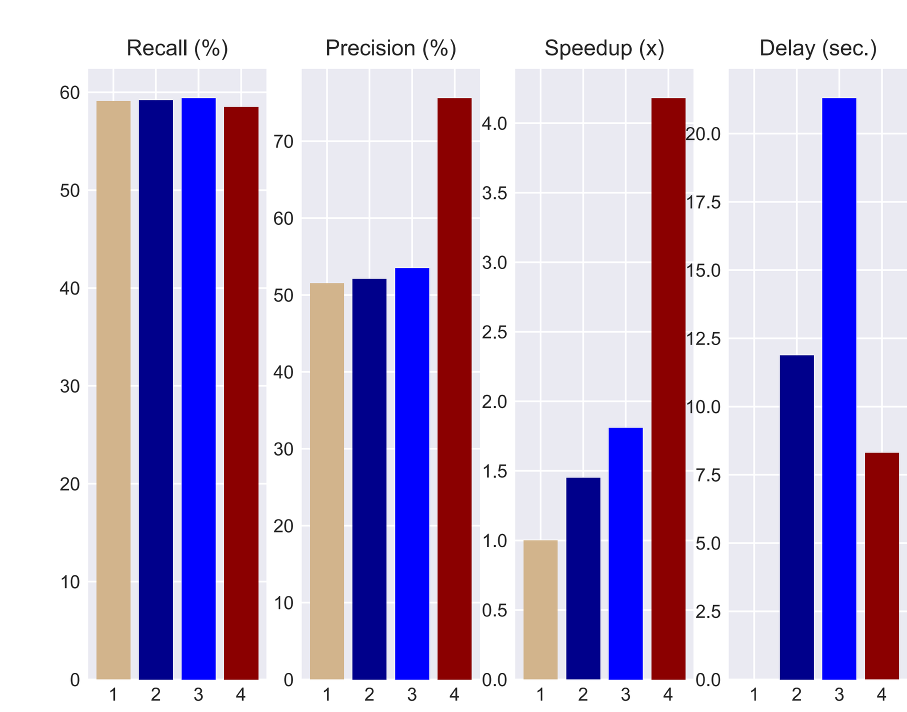
Four schemes:

1) **Baseline** – searches all 8 cameras until t=exit_time*

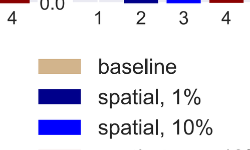
2) **Spatial filter, 1%** - only searches cameras expecting ≥1% of traffic

3) **Spatial filter, 10%** - only searches cameras expecting ≥10% of traffic

4) **Spatio-temp filter, 10%** - in addition to (3), only searches during time window containing [0, 99%] of traffic



*Defined as the average exit time across all 8 cameras in scheme (4).



Observations:

1) **Speedup** factor increases from 1.0 (baseline) → 1.8x (spatial filter) → 4.2x (ST-filter) on 8 cams.

2) Surprisingly, **recall** improves slightly with spatial filtering over the baseline, from 59.1% → 59.4%.

3) Spatio-temporal filtering improves **precision** over the baseline, from 51.5% → 75.6%. Pruning the search space reduces false positive matches.

4) The price of reduced resource usage with ST-filtering is **delay** (lag between tracking and video), from matches found later in pruned search space.

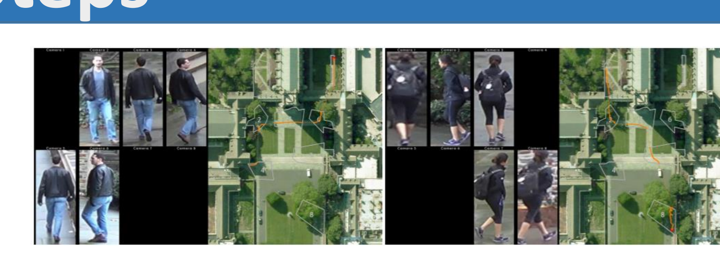
Next Steps

Follow-up work:

1) Use multi-target tracking to build ST-model

2) Mitigate delay with fast-forward search

3) Run scaling experiment on 15+ cam dataset



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