Focus: Querying Large Video Datasets with Low Latency and Low Cost

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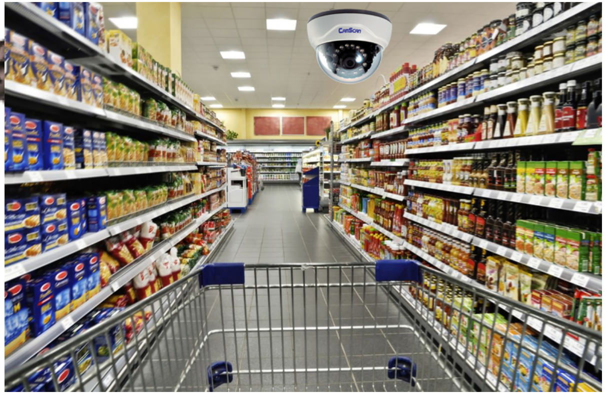
Video Recordings are Ubiquitous

Massive video recordings are happening everywhere

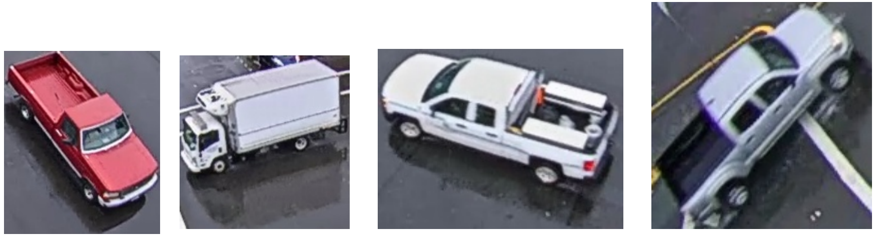


Key Application: Querying Objects in Videos

- Find all trucks among traffic videos in a city last week
- Find all people in garage videos in a company last night

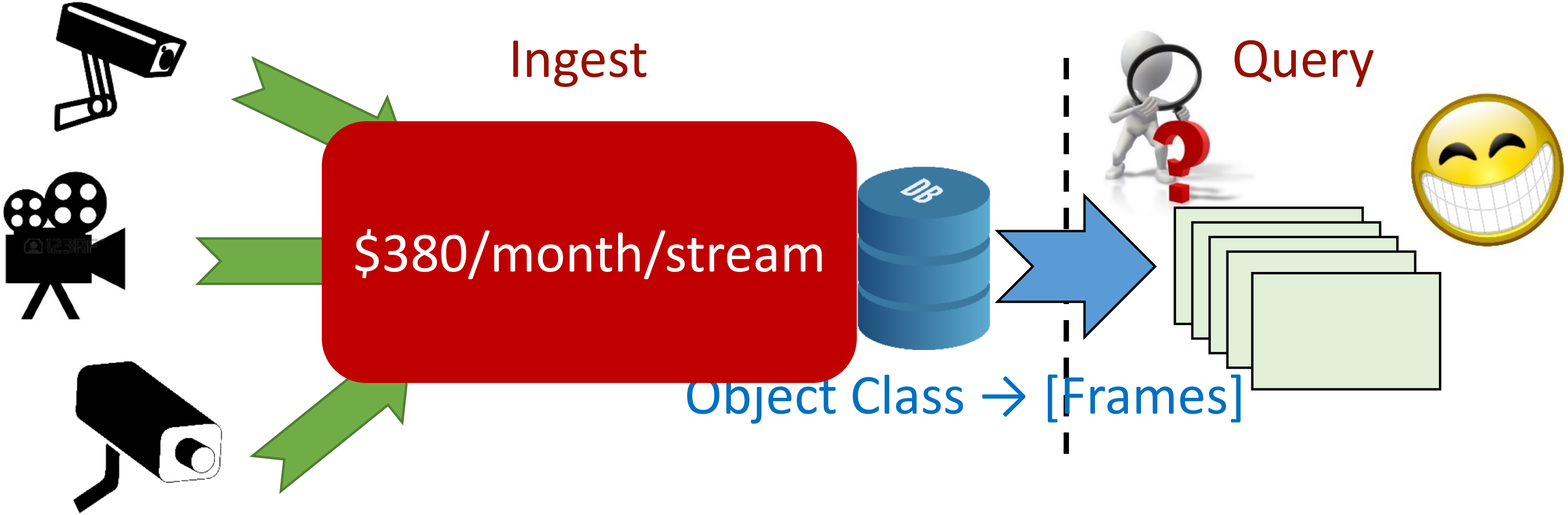
→ *Query execution requires running <u>detector & classifier CNNs</u>*

→ *It is slow and costly on massive videos*



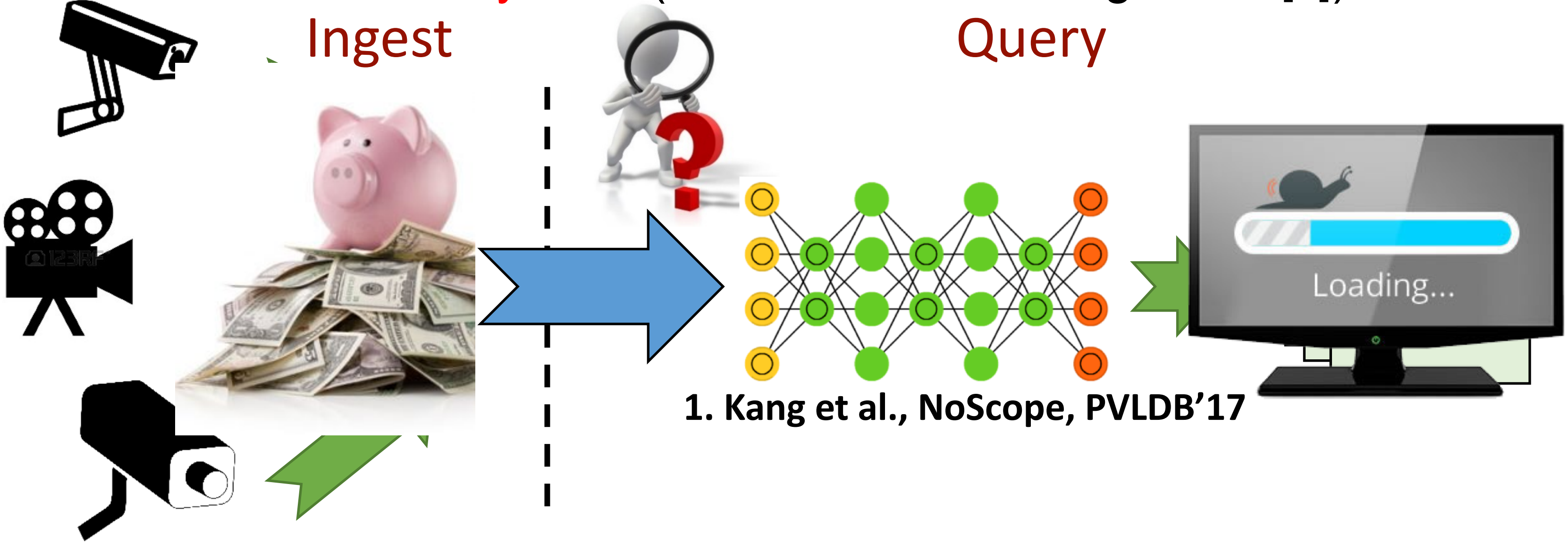
Ingest Time Analysis: Too Costly

- Analyzing live videos at ingest time can make query fast
  - But it is costly
  - Potentially wasteful (ingest all garage cameras vs. query one)



Query Time Analysis: Too Slow

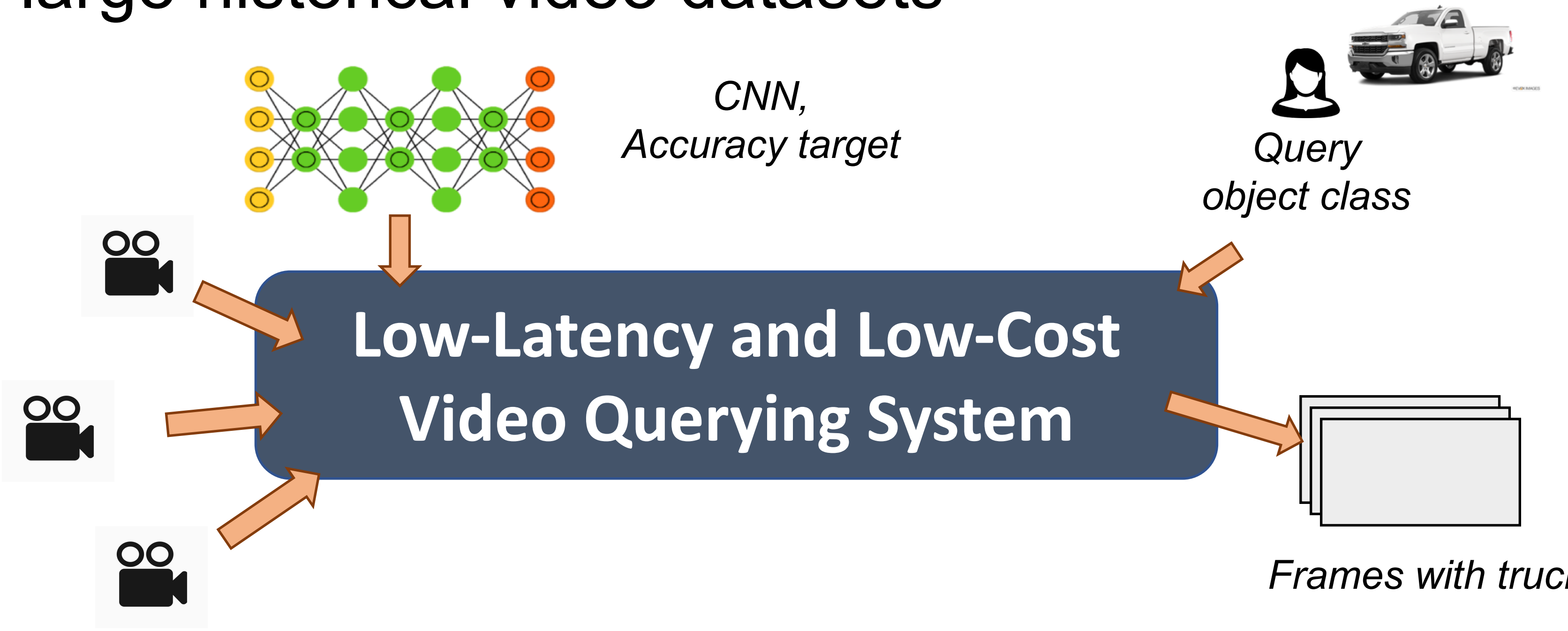
- Analyzing videos at query time can save cost
    - Frame down-sampling / skipping
    - CNN specialization / cascading
    - But it still very slow (5 hr for a month-long video [1])



1. Kang et al., NoScope, PVLDB'17

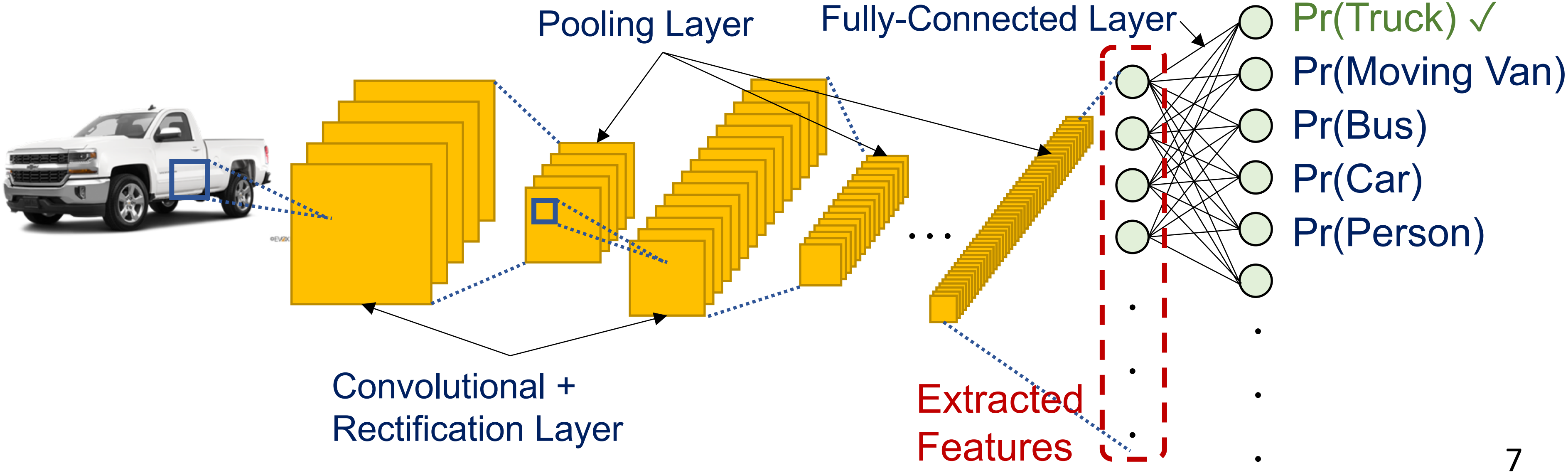
Our Goal

Enable low-latency and low-cost querying over large historical video datasets



Background: Convolutional Neural Networks

- A Convolutional Neural Network (CNN) outputs the probability of each class
- Based on the extracted features (high-level representation)



Focus System: Low-latency query with low-cost ingest

- Approximate indexing via cheap ingest
- Redundancy elimination for fast query
- Trading off ingest cost vs. query latency

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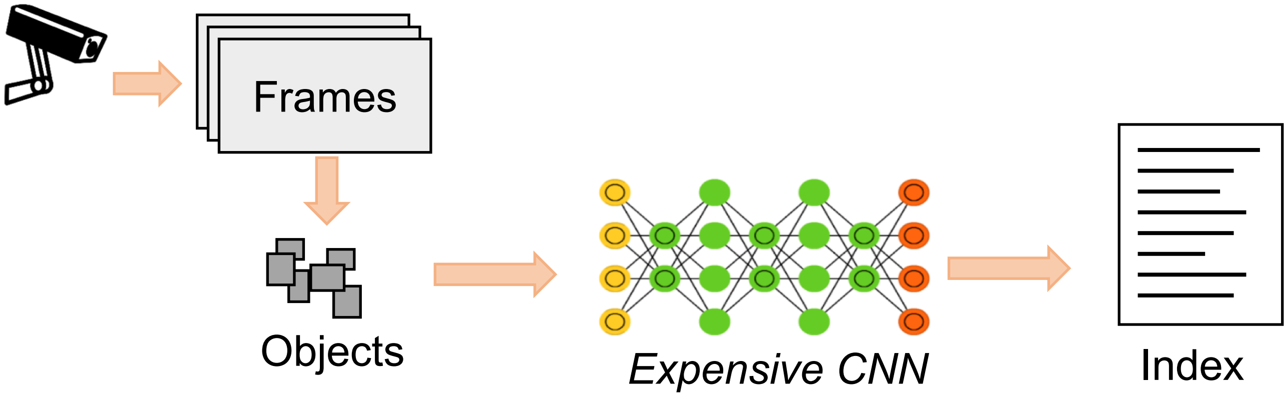
Low-Cost Ingestion: Cheaper CNNs

- Process video frames with a cheap CNN at ingest time
  - Compressed and Specialized CNN: fewer layers / weights and are specialized for each video stream



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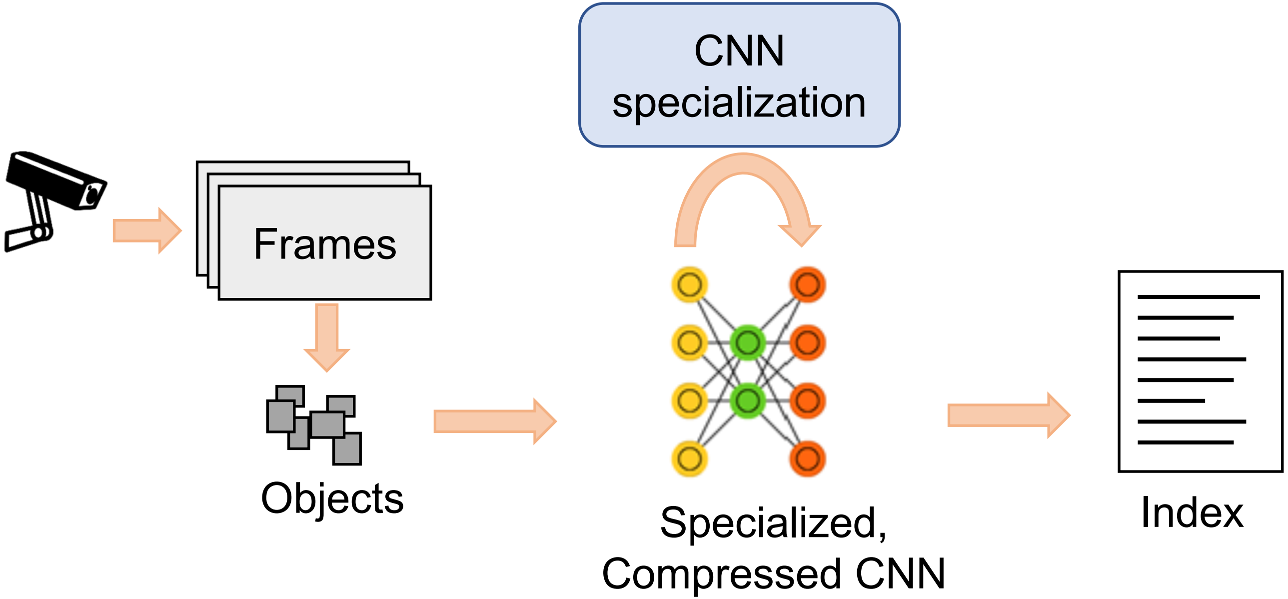


Challenge: Cheap CNNs are Less Accurate

- Cheaper CNNs are less accurate than the expensive CNNs

The best result from the expensive CNN is within the top-K results of the cheaper CNN

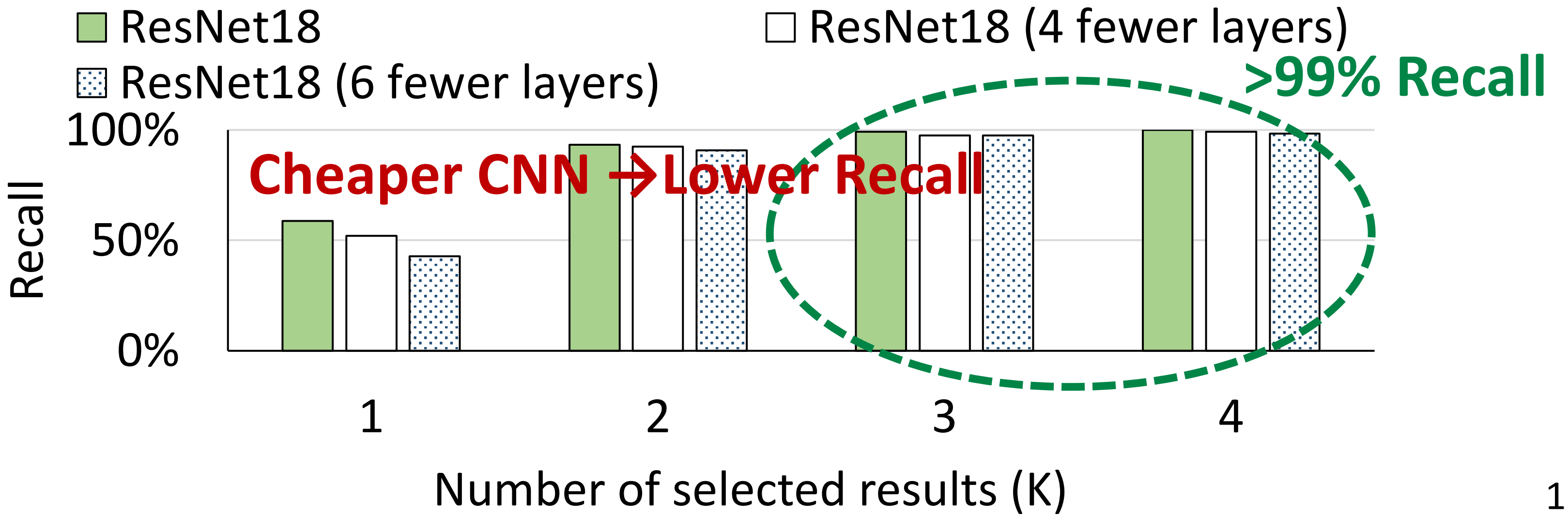
Rank	Expensive CNN	Cheap CNN
1	**Truck**	**Moving Van**
2	Moving Van	**Airplane**
3	Passenger Car	**Truck**
4	Recreational vehicle	Passenger Car

Recall, Precision and Top-K Results

Recall: Fraction of relevant objects that are selected

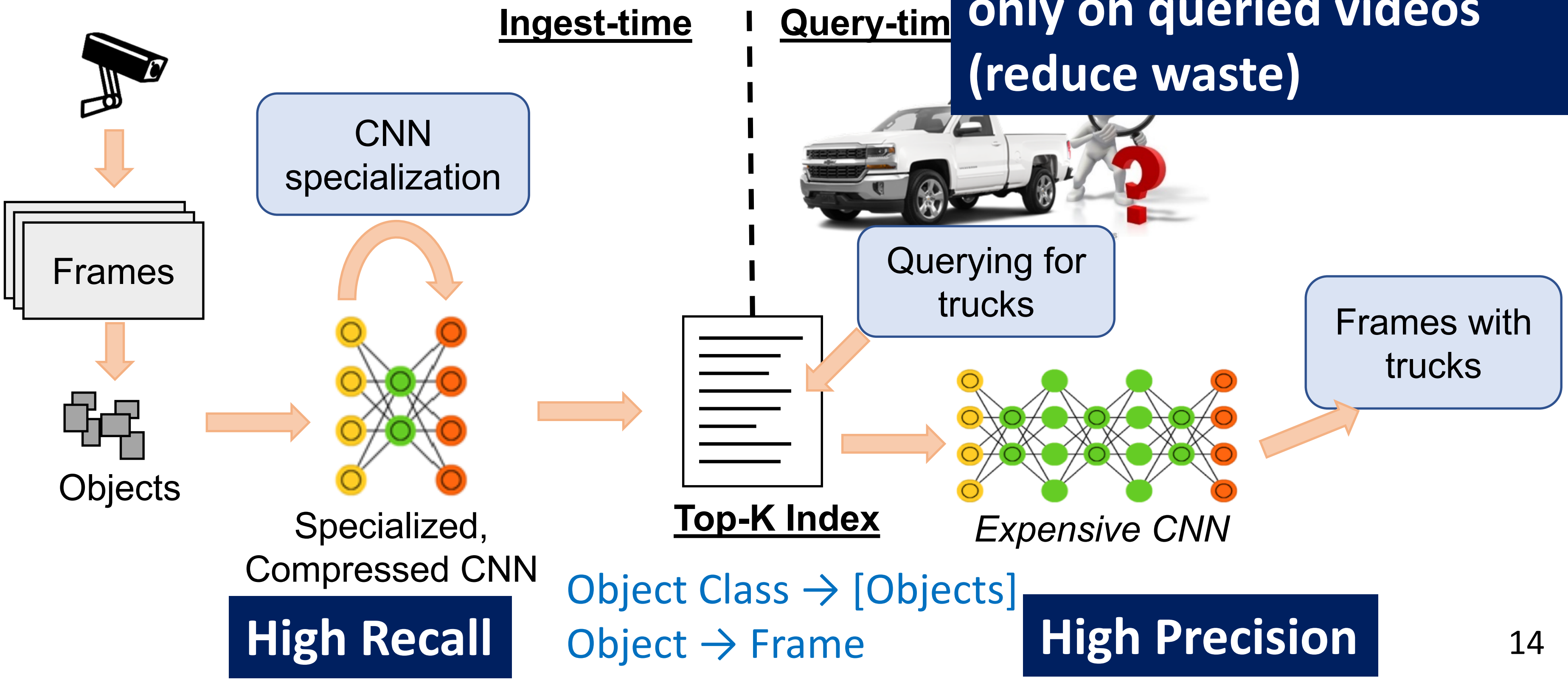
Precision: Fraction of selected objects that are relevant

Ground-truth CNN: YOLOv2



Solution: Split Ingest- and Query-time Work

Query-time work is done only on queried videos (reduce waste)



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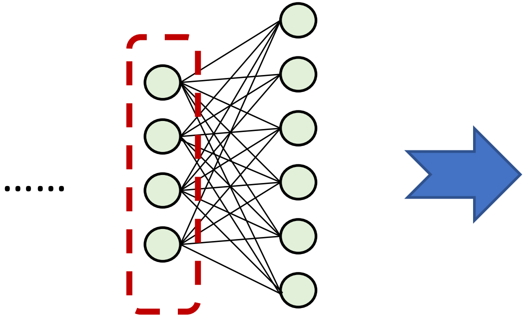
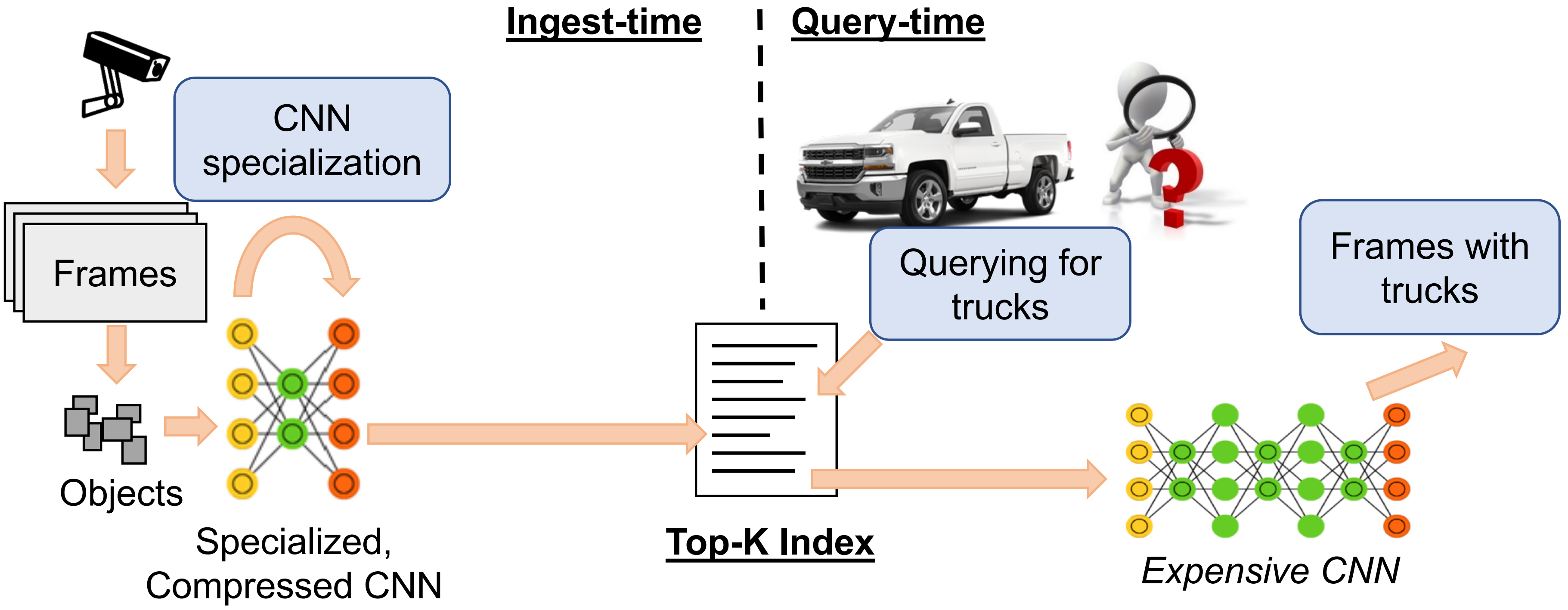
Low-Latency Query: Redundancy Elimination

- Approximate indexing ➔ non-trivial work at query time
  - A larger K ➔ more query-time work
- Images with similar feature vectors are visually similar
- Minimize the work at query time ➔ clustering similar objects based on the extracted features



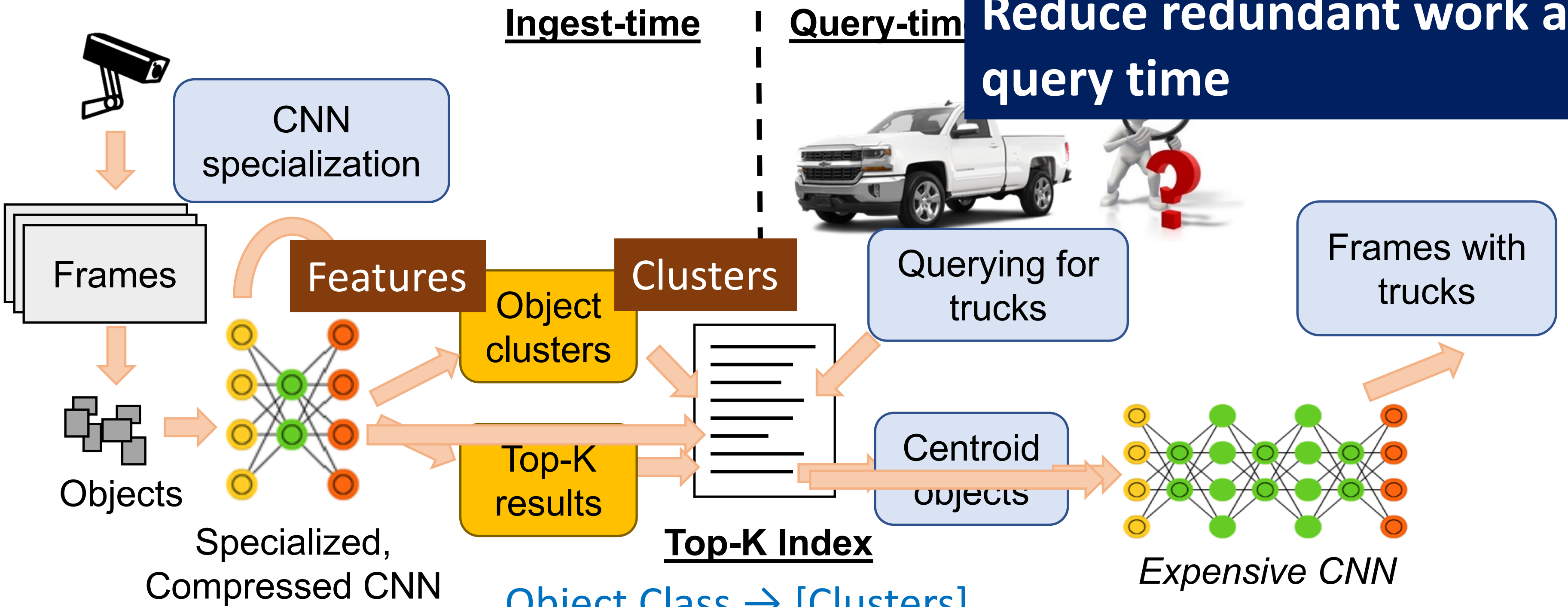
Extracted Features

Adding Feature-based Clustering



Adding Feature-based Clustering

Reduce redundant work at query time



Object Class → [Clusters]

Cluster → Centroid, [Objects], [Frames]

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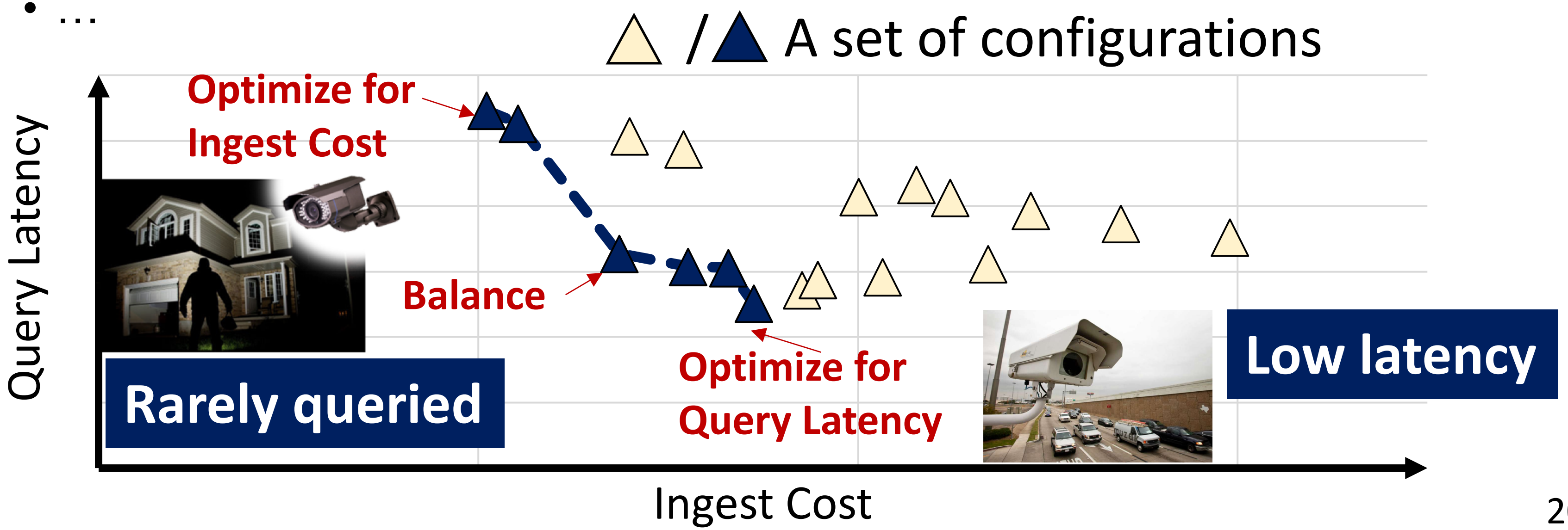
Ingest Cost vs. Query Latency

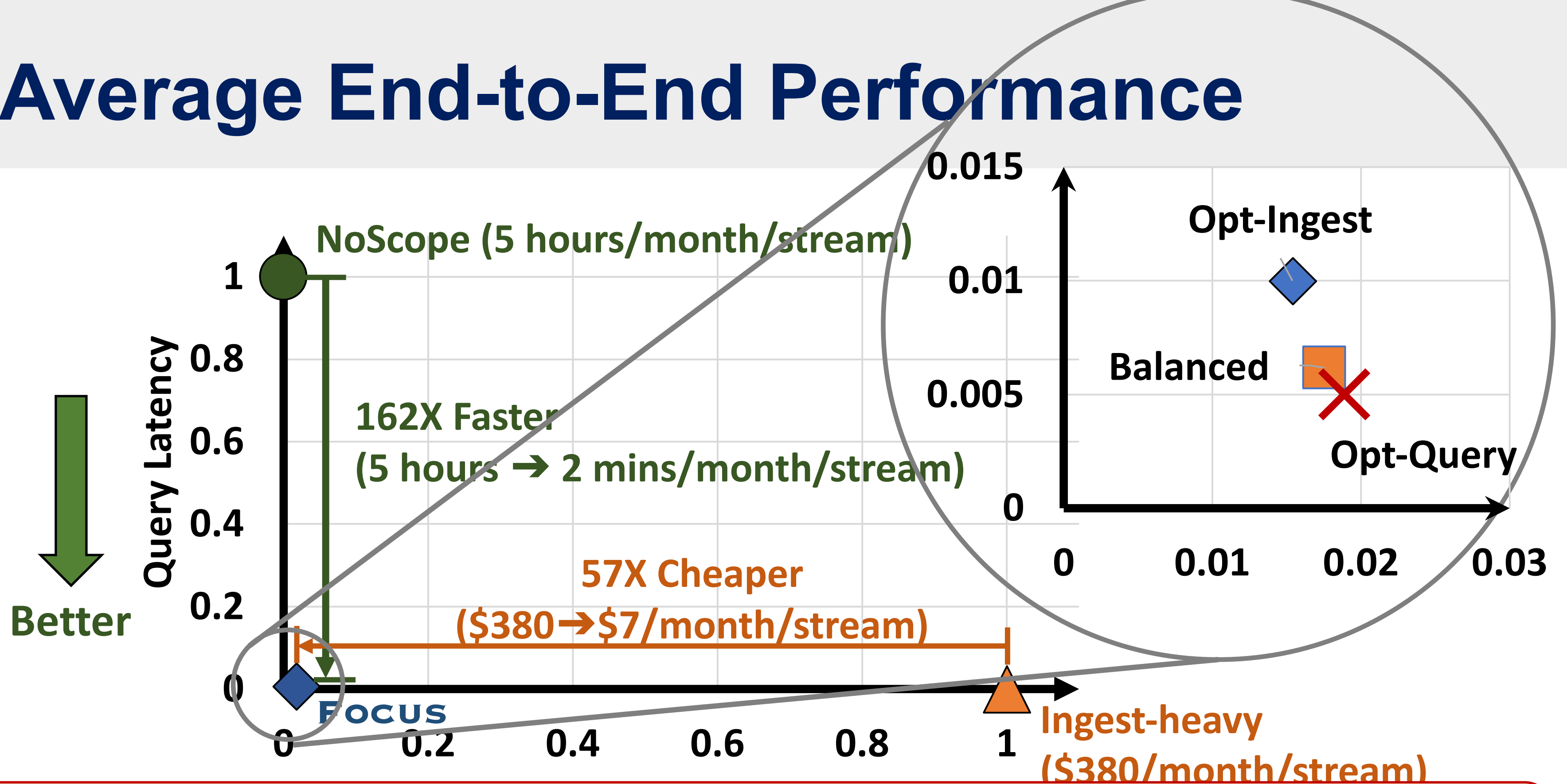
- Parameter selection → trading off ingest cost vs. query latency
  - The cheap CNN at ingest time
  - K in the top-K approximate indexing
  - Clustering threshold for feature-based clustering
  - …



Experimental Setup

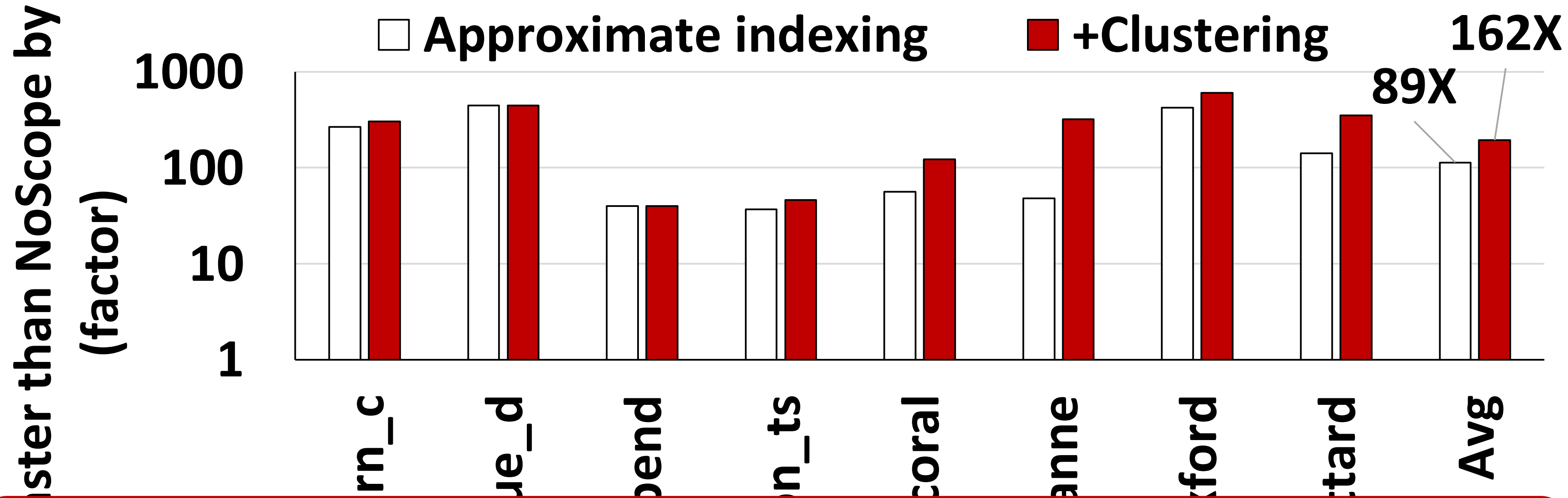
- **Video Datasets**
  - 11 live traffic and enterprise videos
  - Each video stream is evaluated for 12 hours
- **Accuracy Targets**
  - 99% recall and 99% precision w.r.t. YOLOv2
- **Baselines**
  - Ingest-heavy: Analyzes all frames with YOLOv2 at ingest time and stores the inverted index for query
  - NoScope [VLDB'17]: A query-optimized system that analyzes frames only at query time

Average End-to-End Performance



Focus achieves low-latency query with low-cost ingest

Effect of Different Components



Both techniques are important to Focus

Demo

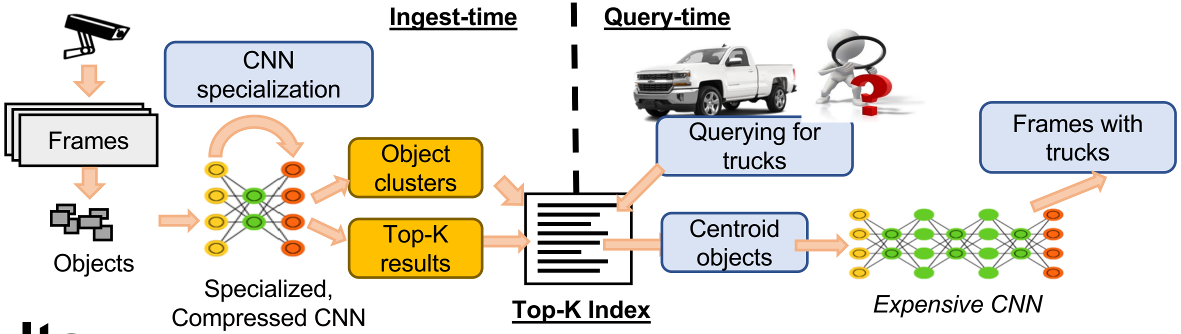
Available at: https://youtu.be/MNCspIm9U38

More in the Paper

- Characterization of real-world videos
- Implementation details
- Other applications
    - Process large and growing data with CNNs, such as audio, bioinformatics, geoinformatics
- More results
    - Trade-off alternatives
    - Sensitivity studies

Key Takeaways

- **Problem**: Querying objects in massive videos is challenging
- **Our Approach**: Low-latency query with low-cost ingest



- **Key Results**
  - 57X (up to 92X) cheaper than ingest-time-only solutions
  - 162X (up to 607X) faster than state-of-the-art, query-time-only solutions

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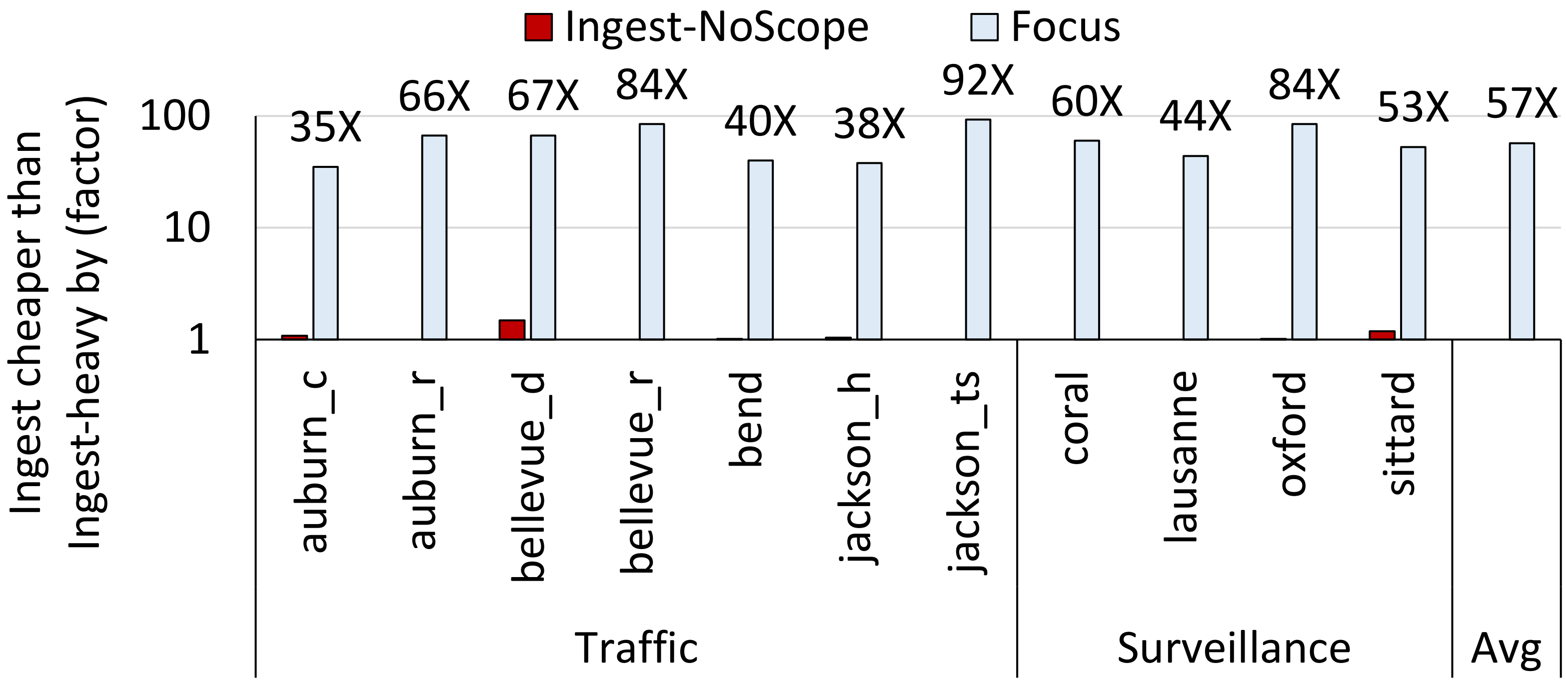
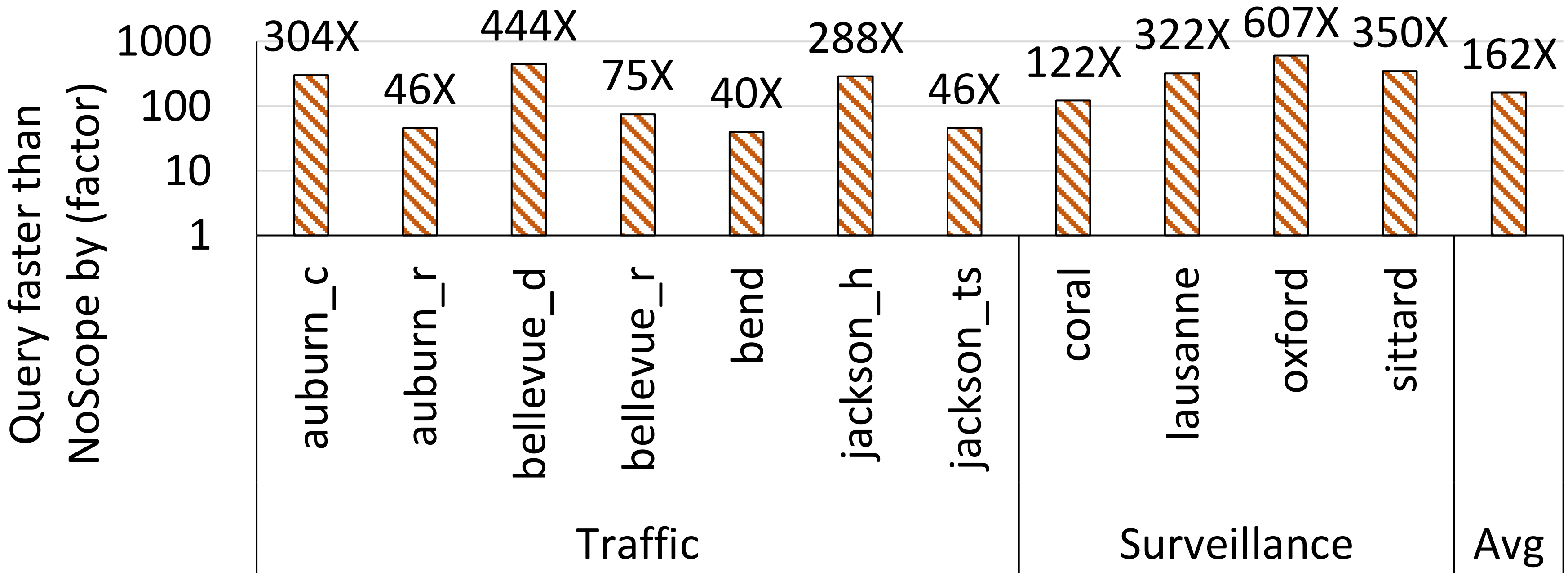
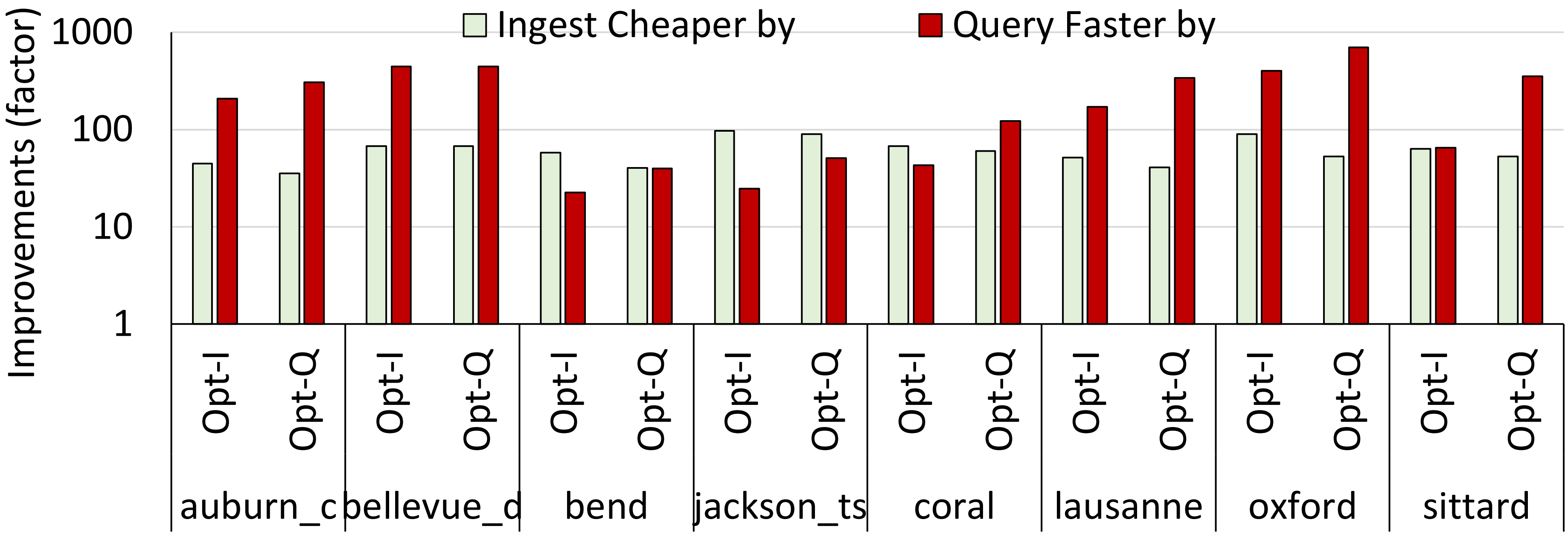
Ingest Cost by Video



Query Latency by Video



Trade-off Alternatives



Sensitivity – Number of Classes

- We study the sensitivity to the number of object class using 1,000 ImageNet classes

- The results show that Focus is
  - 15× faster in query latency
  - 57× cheaper in ingest cost than the baseline systems

Implementation Architecture