[Sc]

STANDARD COGNITION
Building the interface of retail
1. e-commerce level convenience for shoppers
2. e-commerce level automation and insight for retailers
Amazon Go and other shelf-based approaches provide a great proof of concept, but have large drawbacks.
Shelf-based approaches require **thousands** of sensors and a bottom-up restructuring of a store.

Gated entry changes the customer flow.
Our proof of concept store on Market st
27 total sensors
Our partners have consistently requested a ceiling-only solution.

Standard Market is a 1,900 sq foot convenience store.

It’s powered by 27 overhead cameras.

No shelf sensors, depth sensors, RFID, biometric trackers, or turnstiles.
Major Research Challenges in Autonomous Checkout

- Tracking
- Action Recognition
- Item Classification
Major Research Challenges in Autonomous Checkout

Who

Who has what?

What
Major Research Challenges in Autonomous Checkout

Tracking

Action Recognition

Item Classification
Joint work between Karl Obermeyer, Kyle Dorman, Warren Green, Juan Lasheras, Dave Valdman, Jordan Fisher
Major Research Challenges in Autonomous Checkout

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Tracking

- Dense, multi-object tracking in the wild
- Multi-view consensus
- Constant partial and full occlusions
- Has to run in real time
- Can’t use facial recognition
- Off the shelf, cheap hardware
- Has to be nearly 100% accurate
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High level components of a tracker

- Feature Extraction
- Association
High level components of a tracker

Joint Association

Temporal Association

Spatial Association
High level components of a tracker

Feature Extraction

Association

You don’t necessarily want to isolate these systems!
General Approach

- Figure out your metric
- Get good data
- Invest in infrastructure
- Hedge your research bets
- Evaluate true metric
- Productionize
General Approach

• **Figure out your metric**
• Get good data
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Figure out your metric

- You don’t get to pick your metric, you need to determine it

- Whatever metric you pick, it will be leaky. Be prepared

- The standard metric in the literature is probably not what you want
Correct Metric for Cascading Models

Model 1 → Model 2 → Final Metric
Correct Metric for Cascading Models

- Tracking
- Basket System
- Receipt Accuracy
Correct Metric for Cascading Models

- Tracking
- Basket System
- Receipt Accuracy
- Intermediate Metric
Correct Metric for Cascading Models

- Tracking
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Determining your intermediate metric

• Improving the metric should almost always improve your final metric, potentially with the need to retrain downstream models (We call this Firewalling)

• Should be able to be optimized

• Maximize one thing, satisfice everything else. Alternatively, use blended metric.

• Other metrics should be considered “debug” metrics
Things we might care about

- False negatives
- False positives
- Concentration of false negatives per person
- Image plane swaps
- True swaps

- Impossible to optimize everything simultaneously. How do we proceed?
Blended metrics, or utility functions

\[ MOTA = 1 - \frac{\sum_t FN_t + FP_t + IDS_t}{\sum_t GT_t} \]
Blended metrics, or utility functions

$$MOTA = 1 - \frac{\sum_t FN_t + FP_t + IDS W_t}{\sum_t GT_t}$$

Does this assign the right amount of utility to each individual metric? *Probably not.*

Does this firewall our final metric? *Probably not*
Maximize and satisfice

• For all metrics identify the minimum reasonable requirements

• Identify the one additional metric that improving beyond the minimum would yield continued improvement for the downstream systems
Maximize and satisfice

• Satisfice
  • Swaps = 0
  • Untracked people = 0
  • Dropped tracks = 0

• Maximize
  • Sum of image plane MOTA's

• Debug metric
  • Image plane swaps, false positives
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Results
General Approach

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- Get good data
- Invest in infrastructure
- Hedge your research bets
- **Evaluate true metric**
- Productionize
General Approach

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Problem

• Algorithm is $O(n^2 \times p^2)$

• Runs at 0.5 FPS, needs to run at 30 FPS
Solution

• Modify the algorithm to reduce runtime complexity?
Noop.
If we can get a 100x speedup, we don’t need to modify the algorithm.
Why Rust?

1. Very fast
2. Fearless parallelism
3. Easier to maintain
4. Language of choice
Why not Rust?

1. Poor support for scientific computing
2. Hard to learn
3. Smells “shiny”
Case study

We’re using Rust for high performance system code, but not yet for complex models

Wanted a case study to demonstrate feasibility
Approach

1. Test harness
2. Restructure code to be Rustic
3. Full mypy type coverage
4. Automatic transpilation
5. Iterate with the Rust compiler
6. Hand fix the rest
7. Build needed library FFI’s
8. `dbg!` and `print` pairs to isolate output divergence
class SimpleClass:
    """
    This is a simple class.
    
    Args:
    x: Some number here!
    """
    def __init__(self, x) -> None:
        self.x = x
    
    def some_function(self):
        return self.x
class SimpleClass:
    ""
    This is a simple class.
    ""
    Args:
        x: Some number here!
    ""
    def __init__(self, x: int) -> None:
        self.x = x
    
def some_function(self) -> float:
        return self.x
/// This is a simple class.
pub struct SimpleClass {
    x: usize,
}

impl SimpleClass {
/// Return a new SimpleClass.
///
/// # Arguments
///
/// * `x` - Some number here!
pub fn new(x: usize) -> SimpleClass {
    SimpleClass {
        x: x,
    }
}

pub fn some_function(&self) -> f64 {
    self.x
}
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Results

• 30+ FPS for 20 people and 20 cameras on a single core!

• No parallelism! No algorithmic changes!
What sucked

1. Library ecosystem
2. Poor opencv support, had to hand wrap FFI calls
3. Poor, unergonomic multidimensional array support
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