Enabling Physical Analytics in Retail Stores Using Smart Glasses

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Joint work with

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ACM MobiCom 2014

September 8, 2014

Page Views
Clicks
Purchases

Web Analytics

Location

Demographics

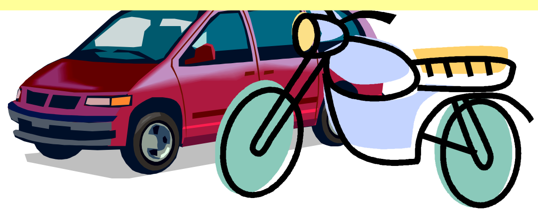
Interests

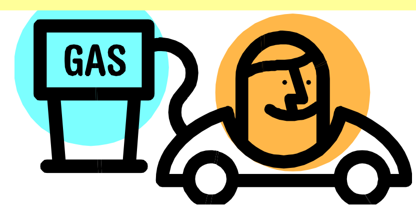
...

Targeted Ads

3x growth in 5 years from 2009 - 2013

Important to capture shopper behavior not only in the online world but also in the physical world





Even excluding those categories:

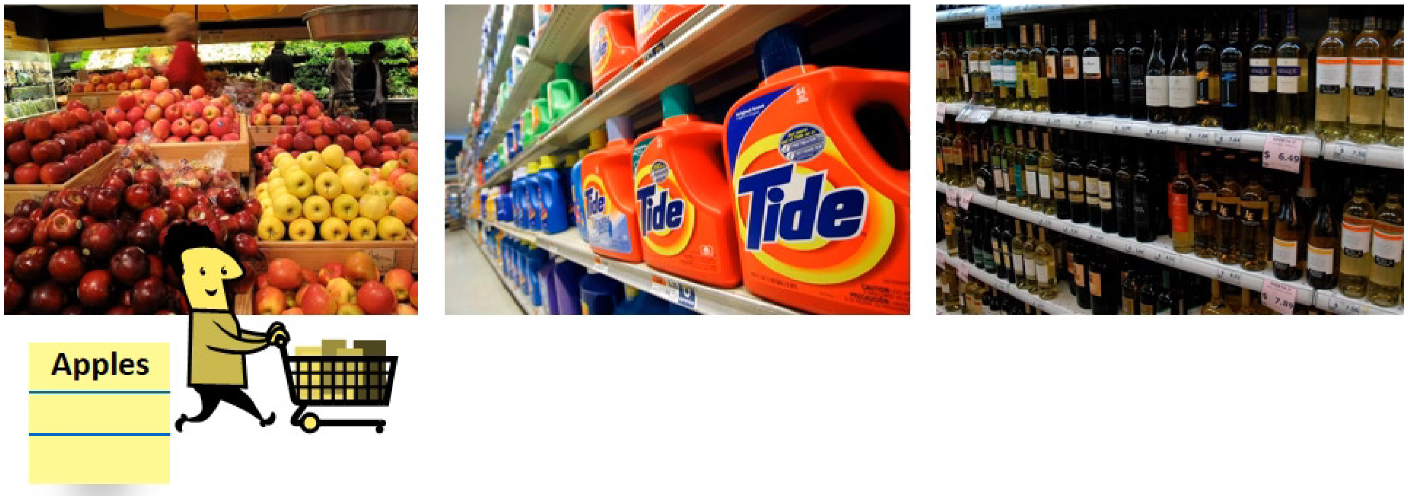
Online sales in U.S. in 2013 only → 11%

Human behavior in the physical world:

- ✓ **Contains signals missed by web-analytics & loyalty programs**
- ✓ **Indicates reinforced interest in buying**

Physical Analytics

Understanding the intent of the shoppers in the physical world



Benefits

Alice sees a coupon as she is about to walk away!

Enable contextual recommendations

Shopping list reminders

Guides to product locations

Our approach

Phytics Engine

Enable a wide coverage and obtain rich user profiles!

Do not tie ourselves closely to any store..

Technology

Localization, Product layouts, User analytics

Incentives

Stores: increased sales

Physical analytics provider: share of profits by partnering with stores

Users: discounts, shopping

Privacy


Survey: Cc

Mar 14, 2014 at 1

Share 37

A new consum
provider Swirl, w
and Ani and Tin
indoor location
consumer acce
overblown.

It is true that c
to their location
clear value for
doing so.

January 17, 2012, 9:00am EST

Shoppers Willing to Tell All

Teresa Novellino
Upstart Business Journal Entrepreneurs & Enterprises Editor
Email | Twitter

It might surprise retailers, but a new IBM study reveals that consumers are much more willing to give up information about themselves.

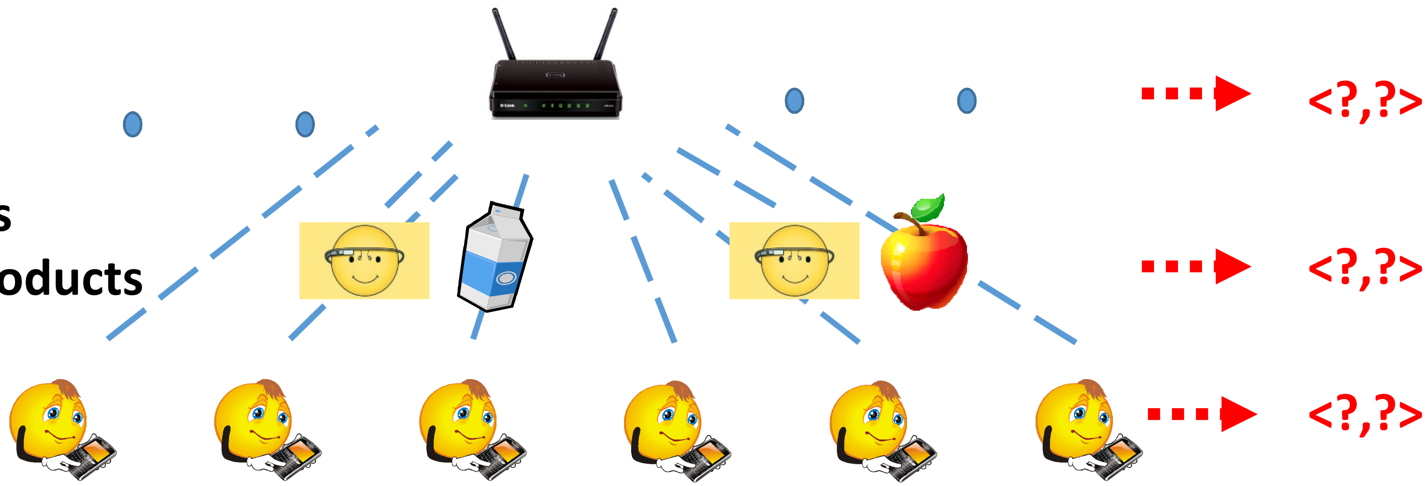
AutoLayout

Behavior Classification

Overview: ThirdEye - AutoLayout

Few Glass users
Glass “sees” products

Many Non-Glass users



Key Idea:

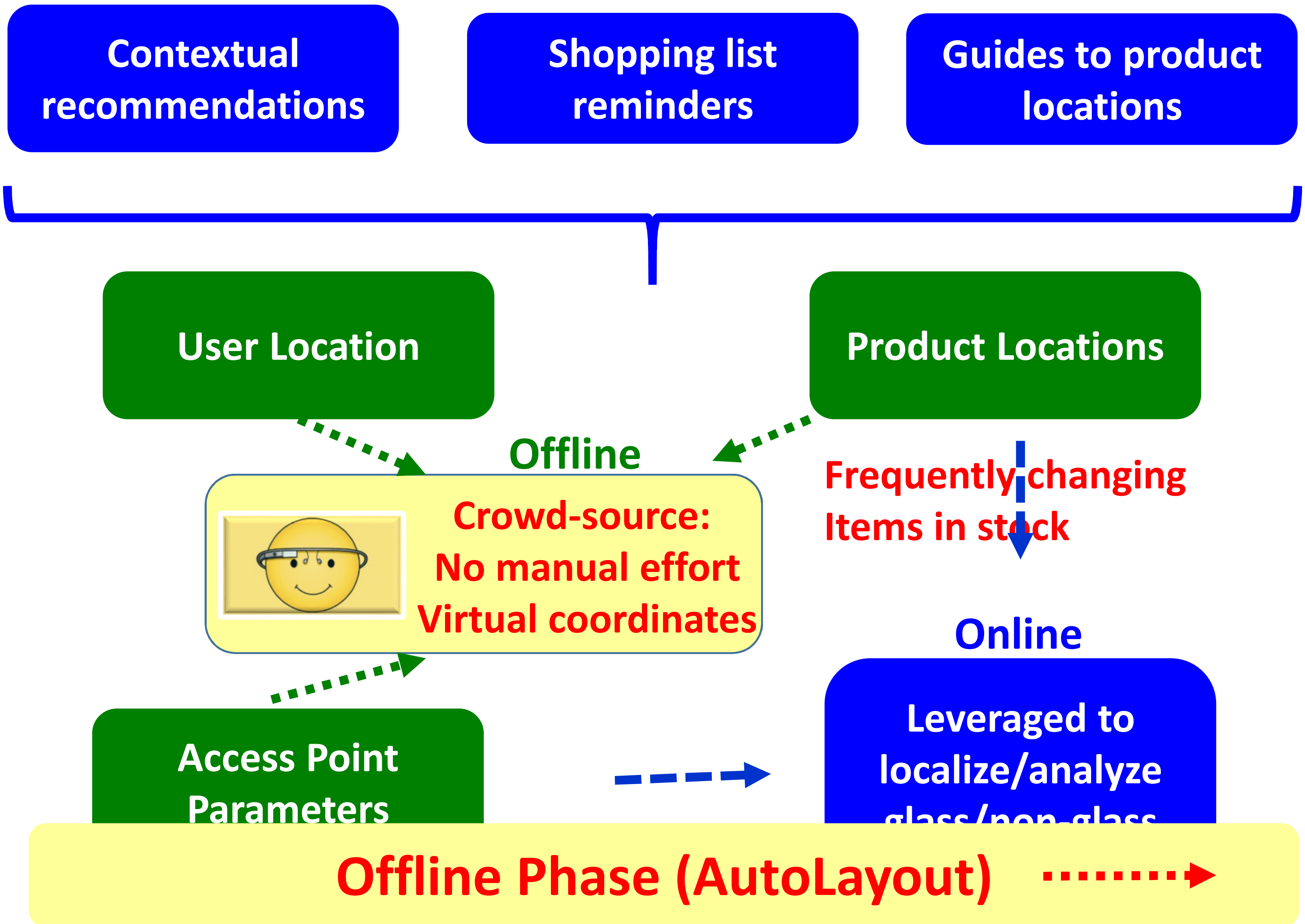
Wi-Fi
+
Inertial sensor
+
Video

Offline: AutoLayout

Localize Glass users
+
Build product map
+
AP locations

Online

Localize Non-Glass users


Contextual recommendations
Shopping list reminders
Guides to product locations
User Location
Product Locations
Offline
Crowd-source:
No manual effort
Virtual coordinates
Frequently changing
Items in stock
Online
Access Point Parameters
Leveraged to localize/analyze
Offline Phase (AutoLayout)

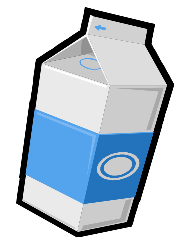
Problem formulation: unknowns

Localization

$sLoc_k^i$: 2D location of k^{th} shopper after i^{th} step

Product layout

$pLoc_j$: 2D location of j^{th} product in store



$< P_l, aLoc_l, \gamma_l >$: parameters of l^{th} *access point*

- γ_l: Path loss constant
- $aLoc_l$: Access point location
- P_l: Transmit power

Critical to localize non-glass users!

Problem formulation

Minimize

Leveraged by [EZ]: ties shopper locations with AP parameters (AP location, AP Tx power, ..)

Wi-Fi term **Inertial sensor term** **Camera term**

$$\mathbf{w_1} \cdot \boxed{\mathbf{r}(\mathrm{sLoc}, \mathrm{aLoc}, \boldsymbol{P}, \boldsymbol{\gamma})} + \mathbf{w_2} \,.\, \mathrm{p}(\mathrm{sLoc}, \mathrm{t}) + \mathbf{w_3} \cdot \mathbf{q}(\mathbf{sLoc}, \mathbf{pLoc})$$

Log Distance Path Loss (LDPL) model: $\mathrm{eRSS}(sLoc, apLoc, apTxPwr, \gamma) = apTxPwr \; - 10\, \gamma \log(\| \; sLoc \; - apLoc \; \|)$

Minimizes error in measured RSS values and those estimated by parameters describing the LDPL model

$$\sum_{l} \sum_{mRSS_{l,k,i} \in W_l} \left\| mRSS_{l,k,i} - eRSS(sLoc_k^i, aLoc_l, P_l, \gamma_l) \right\|$$

l^{th} AP

Over all measured RSS values from that AP across all users

Incorporate mobility: inertial sensors

Minimize

Wi-Fi term — Inertial sensor term — Camera term

$$\mathbf{w_1} \cdot \mathbf{r}(\mathrm{sLoc}, \mathrm{aLoc}, \boldsymbol{P}, \boldsymbol{\gamma}) + \mathbf{w_2} \,.\, \boxed{\mathrm{p}(\mathrm{sLoc}, \mathrm{t})} + \mathbf{w_3} \cdot \mathbf{q}(\mathbf{sLoc}, \mathbf{pLoc})$$

Accelerometer: **step-count [Zee, UnLoc] → distance**

Compass: **heading direction**

For all shoppers, at all steps:

- $\boldsymbol{x_{i+1} \approx x_i + d * cos(\theta)}$
- $\boldsymbol{y_{i+1} \approx y_i + d * sin(\theta)}$

Distance between locations at consecutive steps close to the estimate from the inertial sensors

$$\sum_i \sum_k \left\| sLoc_k^{i+1} - sLoc_k^i - \hat{e}_k^i \right\|^2$$

i^{th}step

k^{th}shopper

$$\hat{e}_k^i = \left[\cos\theta_k^i \ \ \sin\theta_k^i\right]^T$$

Tie in product locations: camera

Minimize

Wi-Fi term / Inertial sensor term / Camera term

$$\mathbf{w_1} \cdot \mathbf{r}(\mathrm{sLoc}, \mathrm{aLoc}, \boldsymbol{P}, \boldsymbol{\gamma}) + \mathbf{w_2} \, . \, \mathrm{p}(\mathrm{sLoc}, \mathrm{t}) + \mathbf{w_3} \cdot \boxed{\mathbf{q}(\mathbf{sLoc}, \mathbf{pLoc})}$$

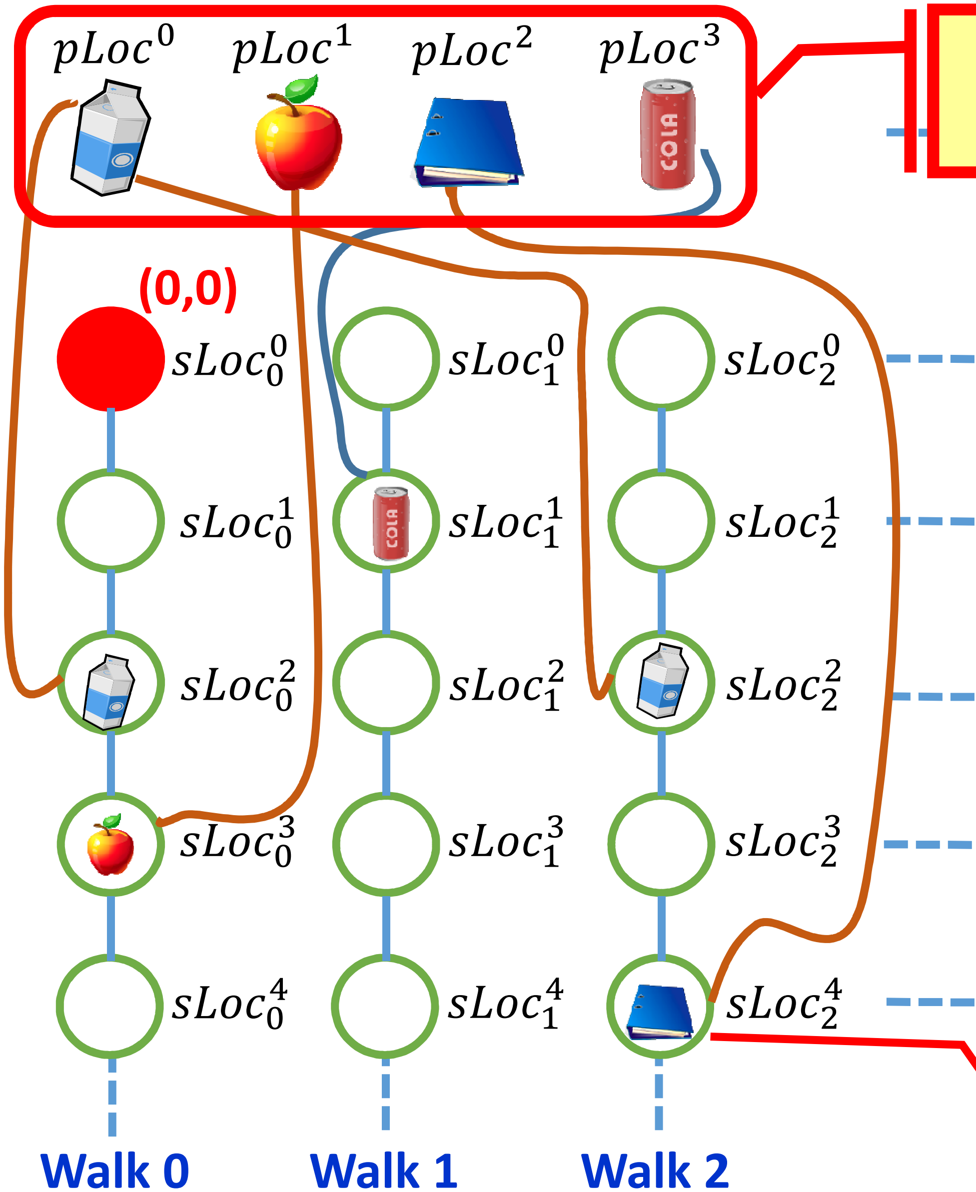
Leverage Google Reverse Image search to obtain labels for product images

All shopper locations from where a particular product was seen must be close to each other

$$\sum_{j} \sum_{<k,m> \in L_j} \left\| sLoc_k^m - pLoc_j \right\|^2$$

j^{th}product $\qquad$ k^{th}shopper saw j^{th}product at m^{th}step

Optimization



Leverage product locations to align different walks

- Origin: $sLoc_0^0 = (0,0)$
- Leverage mobility: Locations within a walk are connected via inertial sensor data

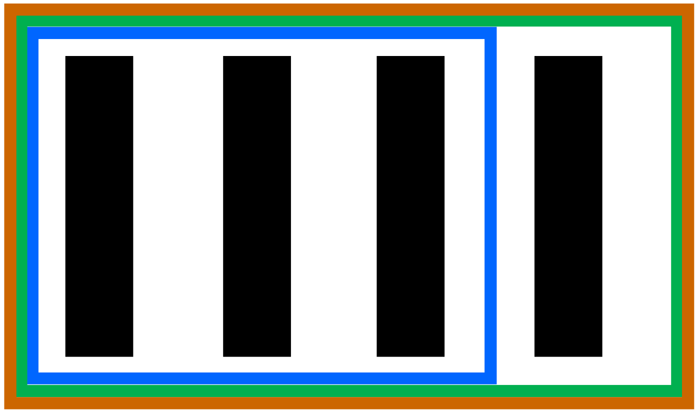
- Run BFS to initialize all shopper & product locations

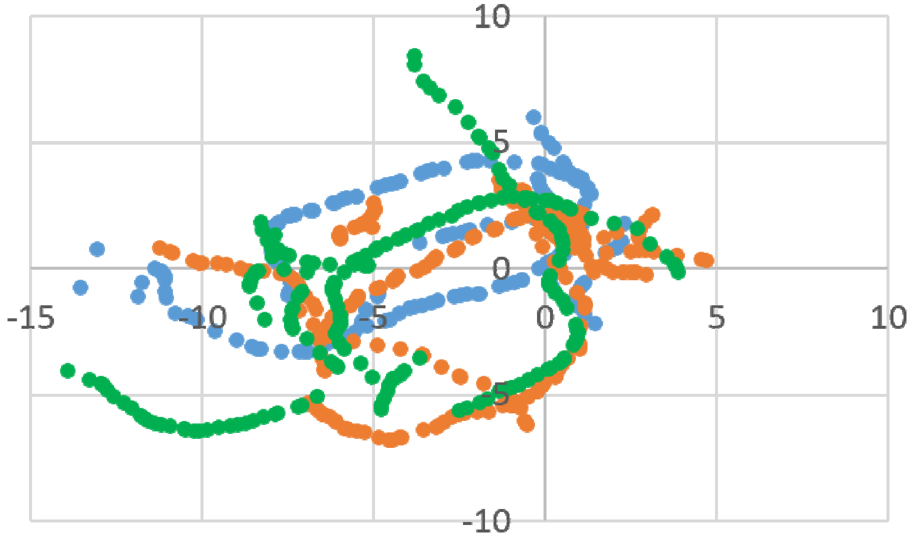
- Gradient descent: refine initial estimates

Notebook seen by shopper 2 after 4 steps

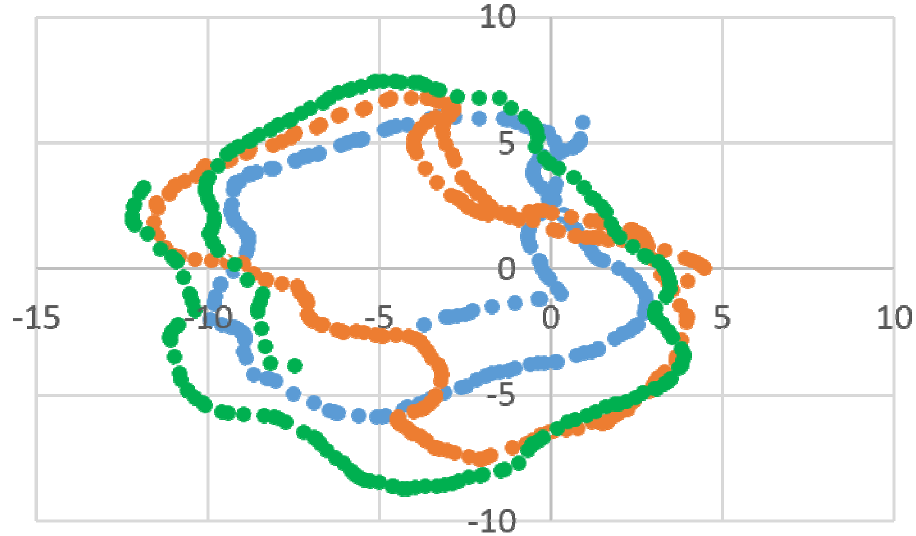
Example walks around aisles in Target

Actual walks around aisles



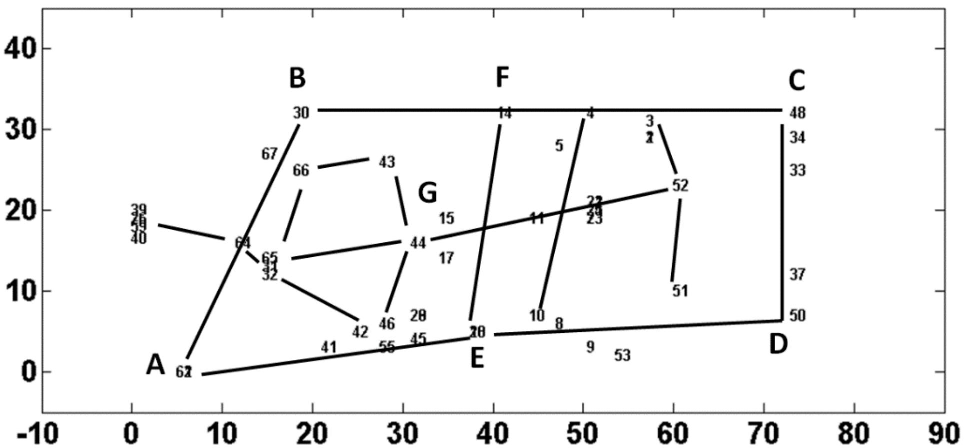


After BFS: all tracks are in same coordinate system

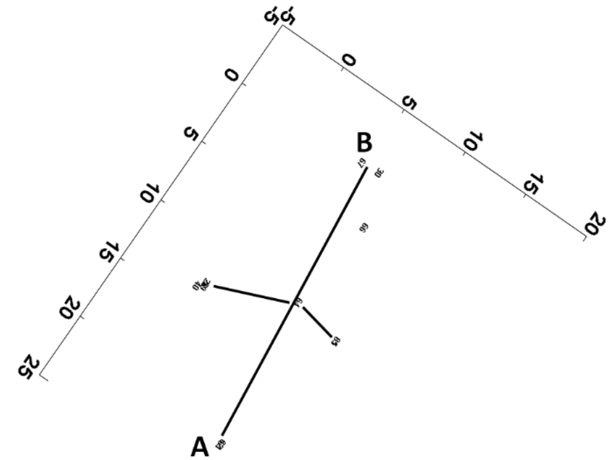


After optimization: tracks look closer to actual walk

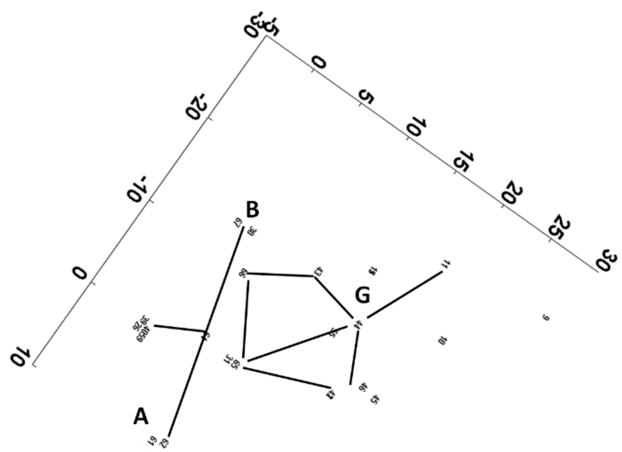
Inferred layout for H-E-B: improves with more shoppers



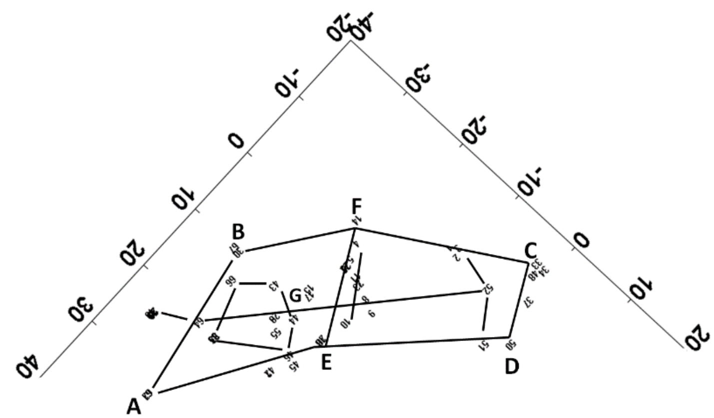
Actual Layout



2 Shoppers



4 shoppers

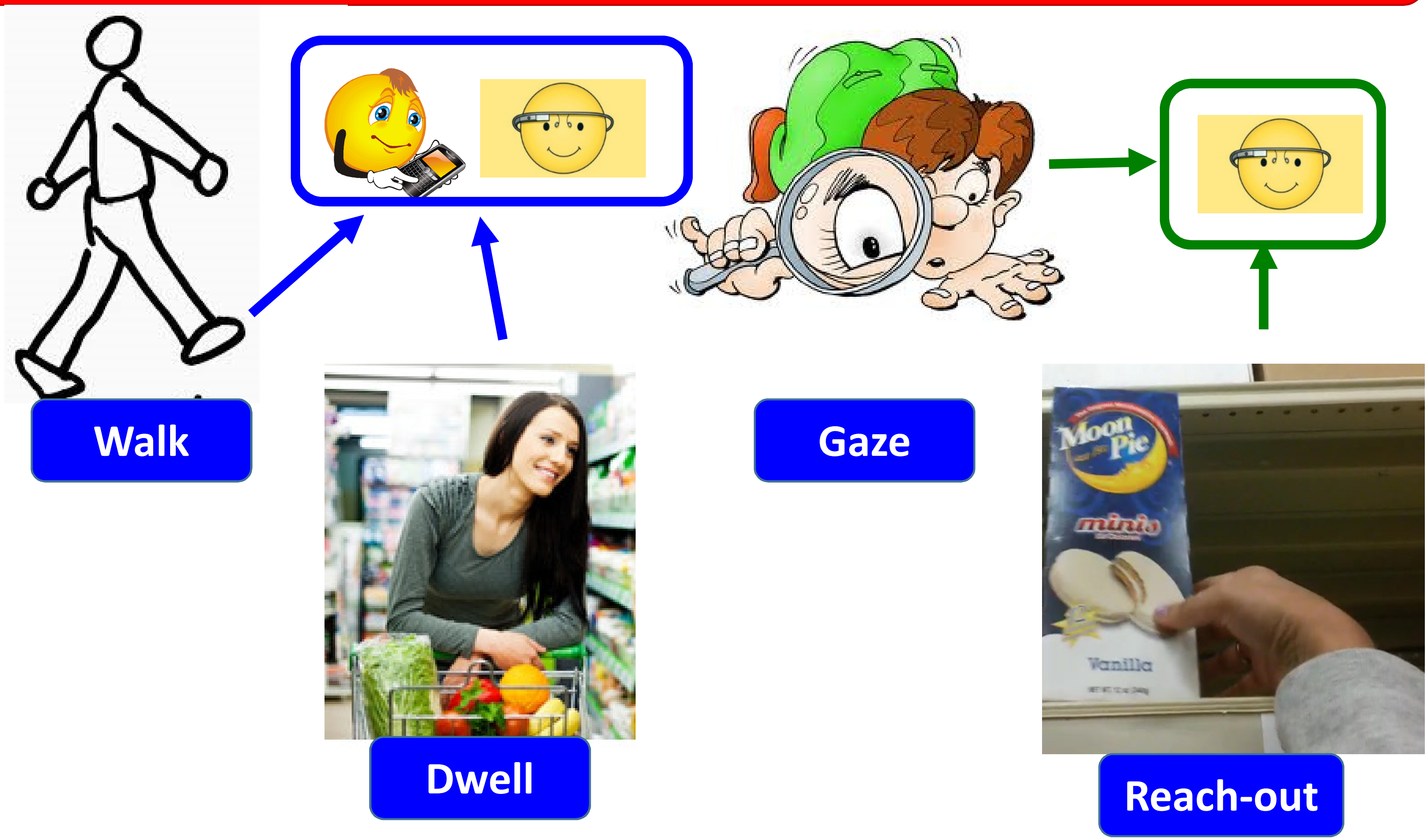


7 shoppers

AutoLayout

Behavior Classification

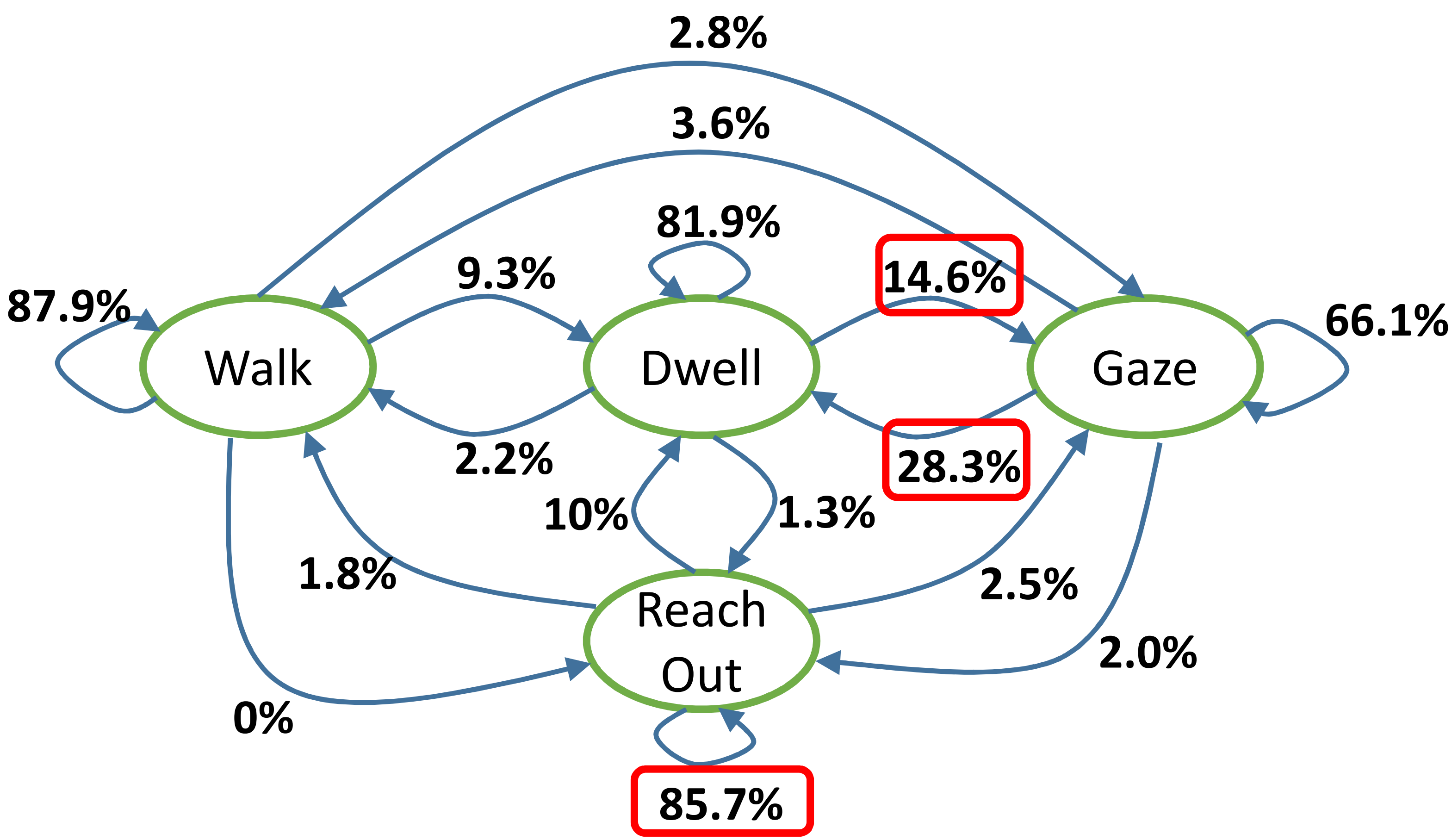
Overview: ThirdEye - User analytics



In a retail setting

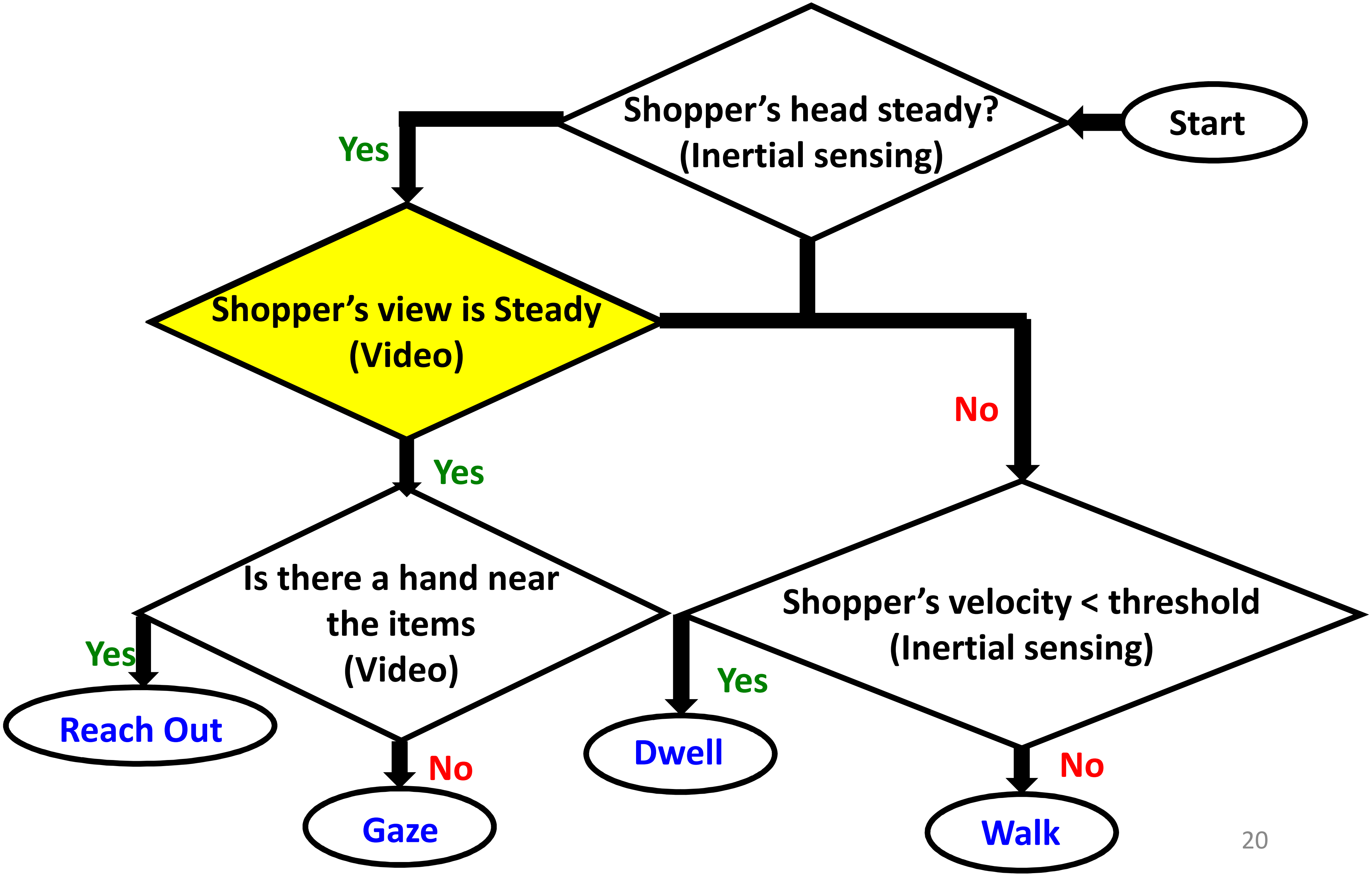
Analyzed 3 hours of shopping videos from 7 shoppers wearing Google Glass from 2 large stores: H-E-B and Target

Time spent: dwell (50.7%) > gaze (23.7%) > walk (17.3%) > reach-out (8.2%)



- **Most frequent inter-state transitions: dwell and gaze**
- **Reaching-out: tend to remain in the state for few seconds**

Behavior classification algorithm



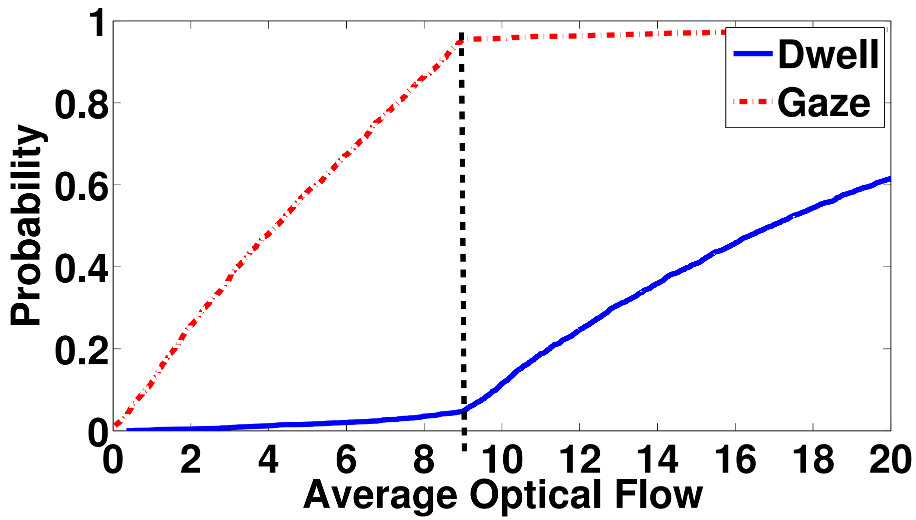
Gaze and Reach-out

When shopper is gazing/reaching-out scene in front of him does not change

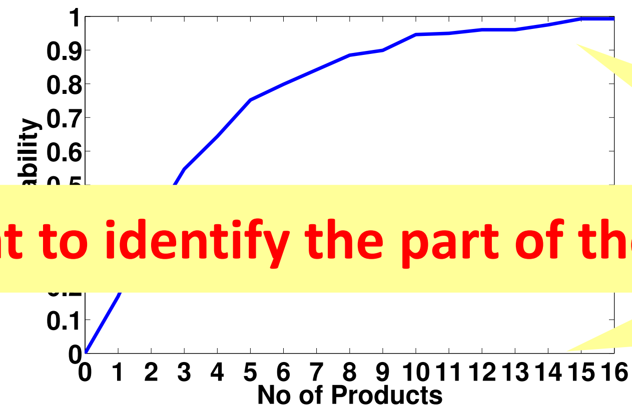
Leverage vision based technique Optical Flow to detect gaze/reach-out

- Optical flow (of): difference in terms of pixels between consecutive images
- If $of < of_{gaze}$ detect gaze/reach-out

88% detection rate at 1.8% false detections



Attention identification



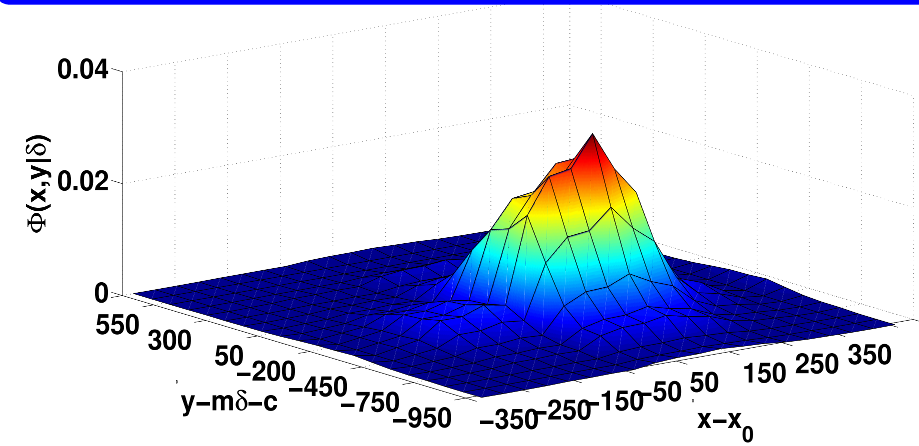
A frame may

Important to identify the part of the frame that user was interested in!

as 16 items!

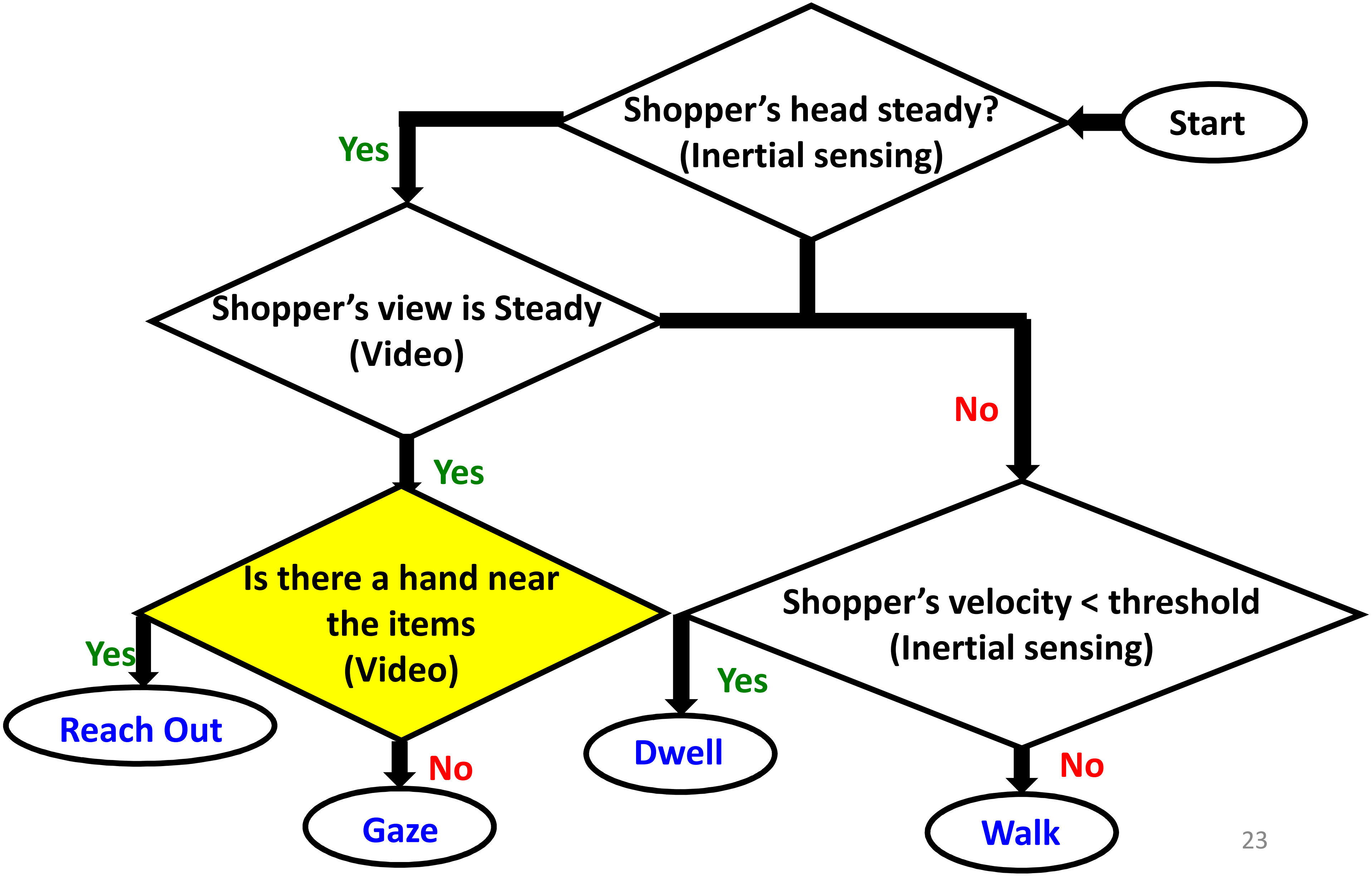
- Estimated X: center of frame with offset for camera position
- Estimated Y: Function of head tilt

PDF of error in X, Y estimates



Accuracy of product identification: Top 1: 76%, Top 3: 90%

Behavior classification algorithm



Reach-out detection

Reach-out indicates high degree of interest: important to detect

Hand seen in the frame:

— **detect hands to detect reach-out**

Train TextonBoost Classifier

Leveraging TextonBoost classifier

Divided hand

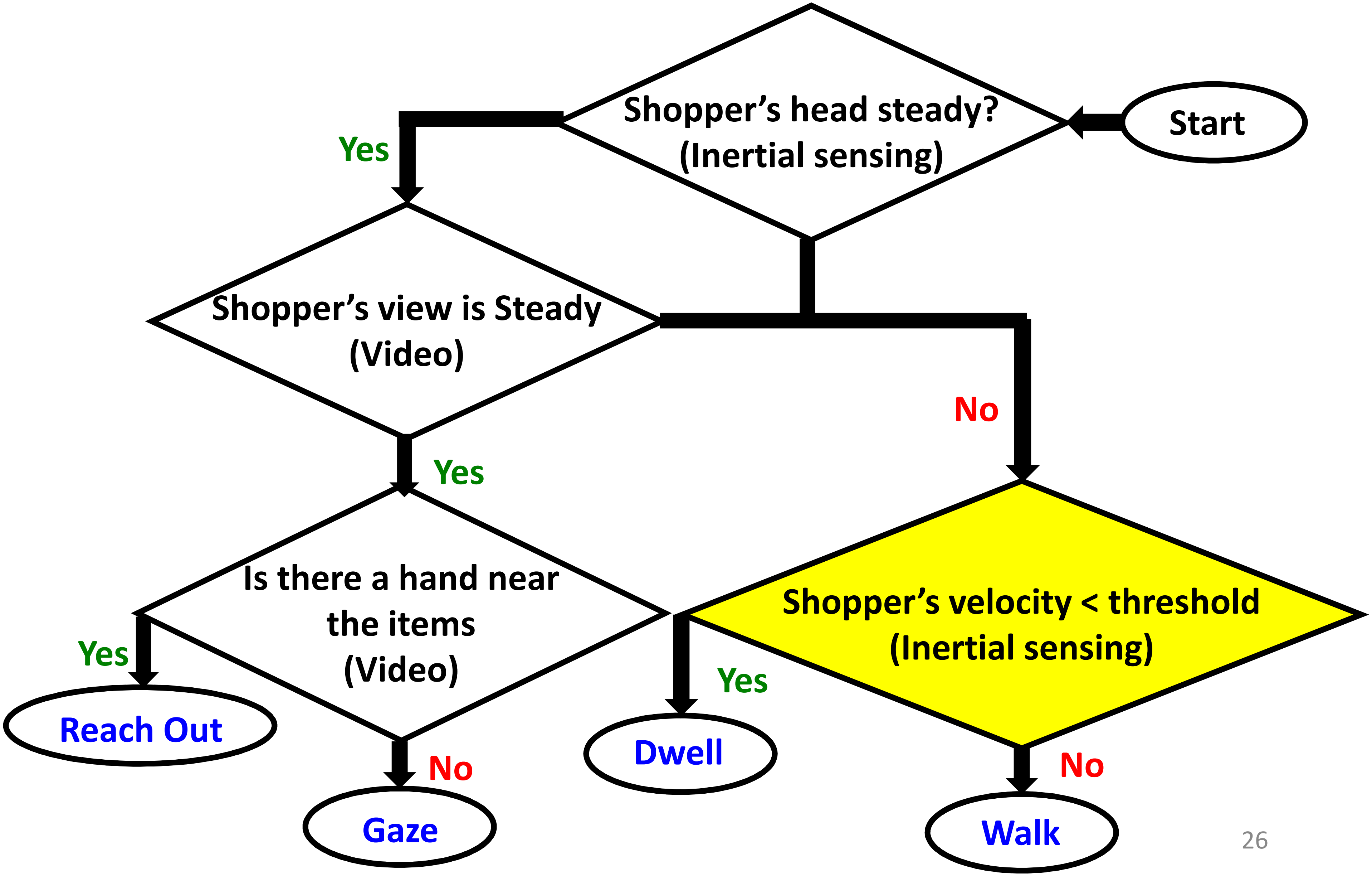
Cluster together nearby segments

Spurious hand

Ignore very small segments

Detection success rate: 86% False detection rate: 15%

Behavior classification algorithm



Dwell detection

Accelerometer showing that user is static?

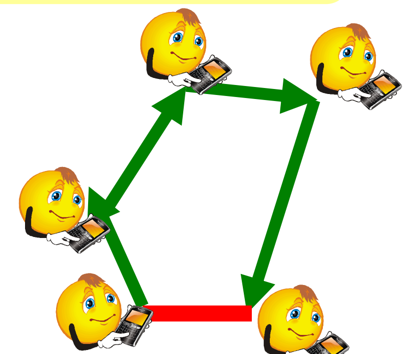
Shopper may not be static, he may take few steps looking at nearby items

Dwell characterized by small net displacement!

Detect dwell based on periods of low net displacement

Suppose K steps in time window τ and heading at step *i* is θ_i

— Detect steps using prior work Zee [MobiCom 2011]



Net displacement in 5 sec

Magnitude of net velocity vector

$$\|v\| = \sqrt{\left(\sum_{i=1}^{i=K} \cos\theta_i\right)^2 + \left(\sum_{i=1}^{i=K} \sin\theta_i\right)^2}$$

Dwell if:

$\|v\| < \|v\|_{dwell}$

95% detection rate at 10% false alarms

Related work

Research

- Localization [MobiSys12, MobiCom10, MobiCom12, ..]
- Vision [ICCV09, ICCV13, ..]
- Robotics [UbiComp09, ..]
- Human-activity sensing [Sensys07, ..]
- Shopping-behavior [UbiCom08, Pervasive Computing11, ..]

Industry

iBeacon

Get In-Store Notifications

Point Inside

Conclusion

Our contributions

- Fuse Wi-Fi, inertial sensor and video data from smart glasses
- AutoLayout: Map the store without any user or store input
- Use these inferences to track glass/non-glass users in online phase
- Characterize walk, dwell, gaze and reaching-out activities of shoppers
- Attention identification within the captured frame

Future work

- Larger data-set for patterns representative of more diverse population
- In-depth analytics of shoppers

Thank You!

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