The 26th
Symposium on Sensing
via Image Information
SSII 2020

構造化３次元復元と Anytime/Anywhereナビゲーション

2020.6.12

古川 泰隆（サイモンフレーザー大学）

The 26th Symposium on Sensing via Image Information
SSII 2020

Computational Motion Sensing & Structured Geometry Modeling

2020.6.12

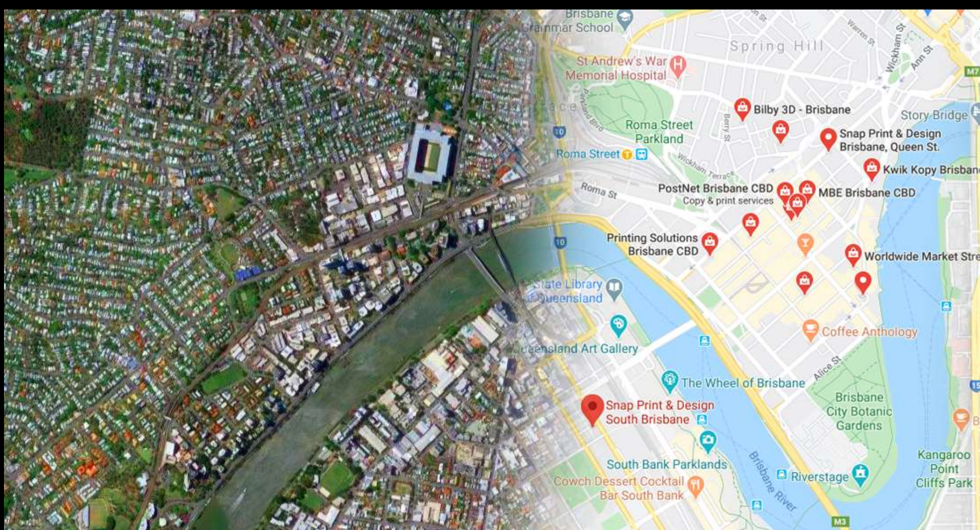
古川 泰隆 （サイモンフレーザー大学）

Indoor walking directions in Google Maps for Android
Google Maps. May 9, 2012. [https://www.youtube.com/watch?v=eMLpo75H4Fc]

2 Fundamental Technologies

Mapping
Content Creation

Localization
Content Selection

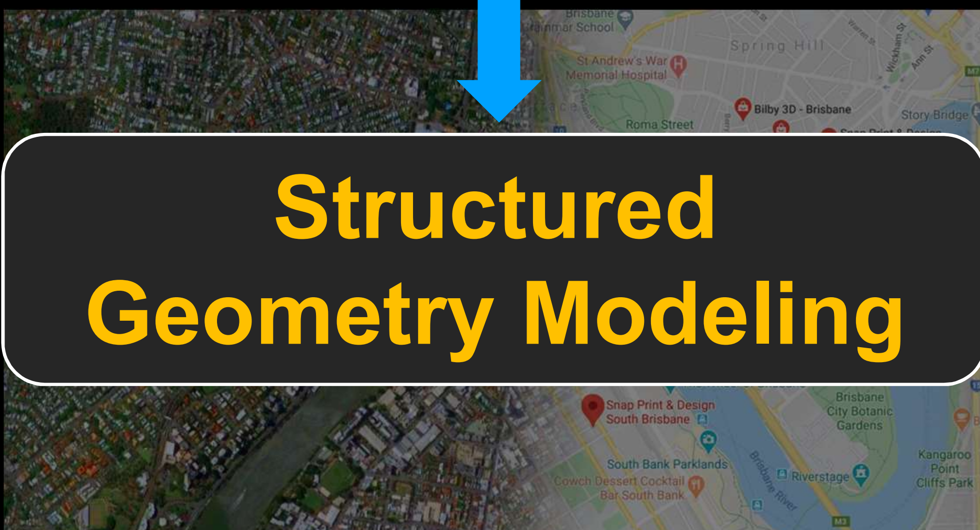


[https://towardsdatascience.com]

2 Fundamental Technologies

Mapping
Content Creation

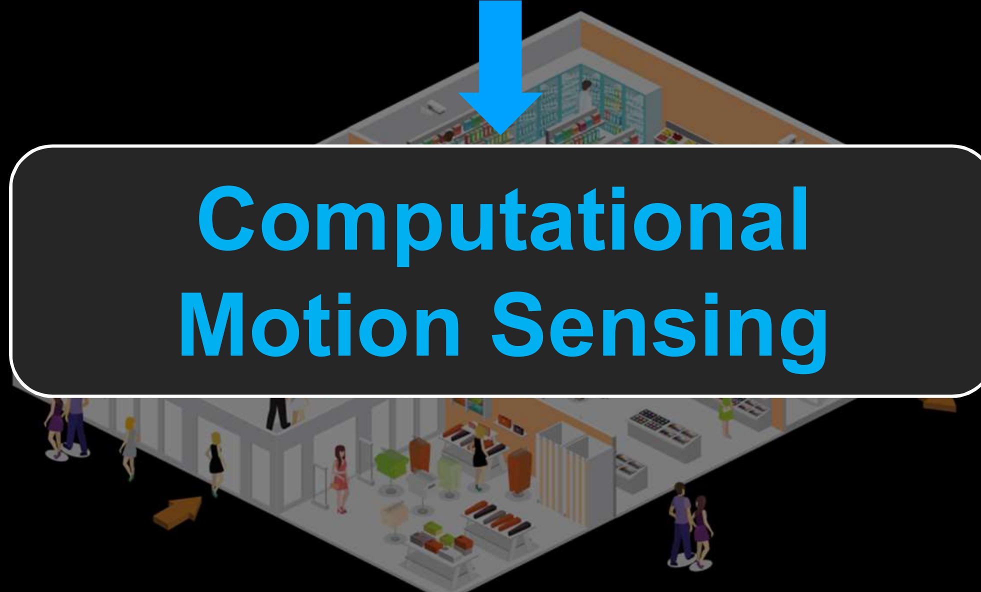
Structured Geometry Modeling



[https://towardsdatascience.com]

Localization
Content Selection

Computational Motion Sensing



Computational Motion Sensing

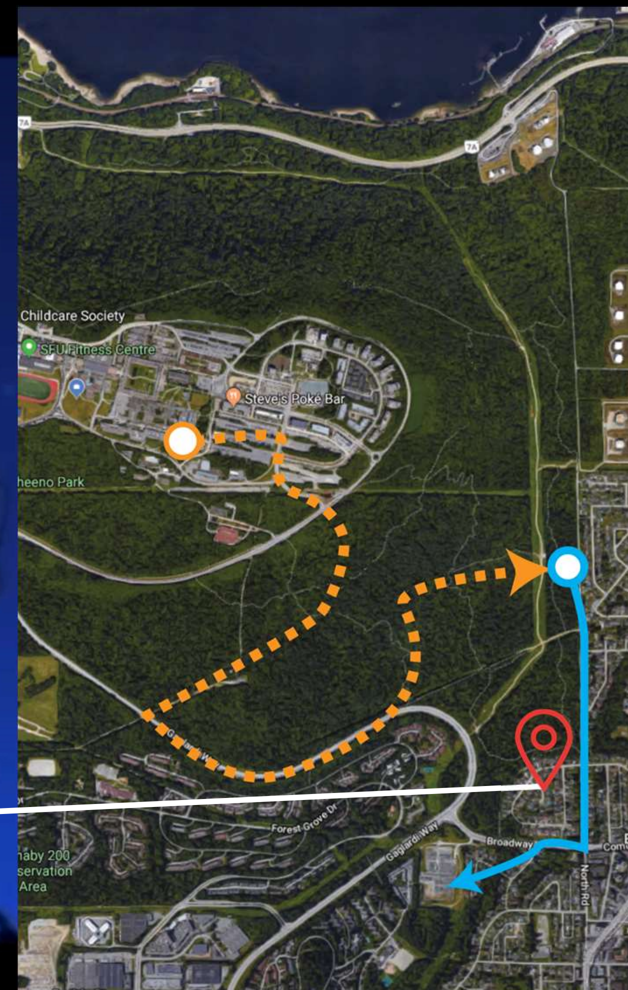
Hang Yan

Qi Shan

Sachini Herath

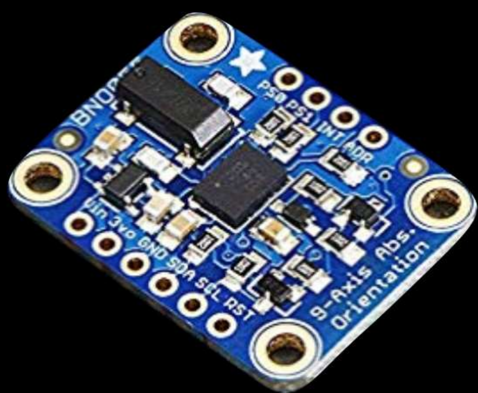
Saghar Irandoust

Pyojin Kim



The Iron Giant


Iron giant
You
1x
RoNIN
Step Counting
IONet
RIDI



1. What is IMU?

2. Existing approach

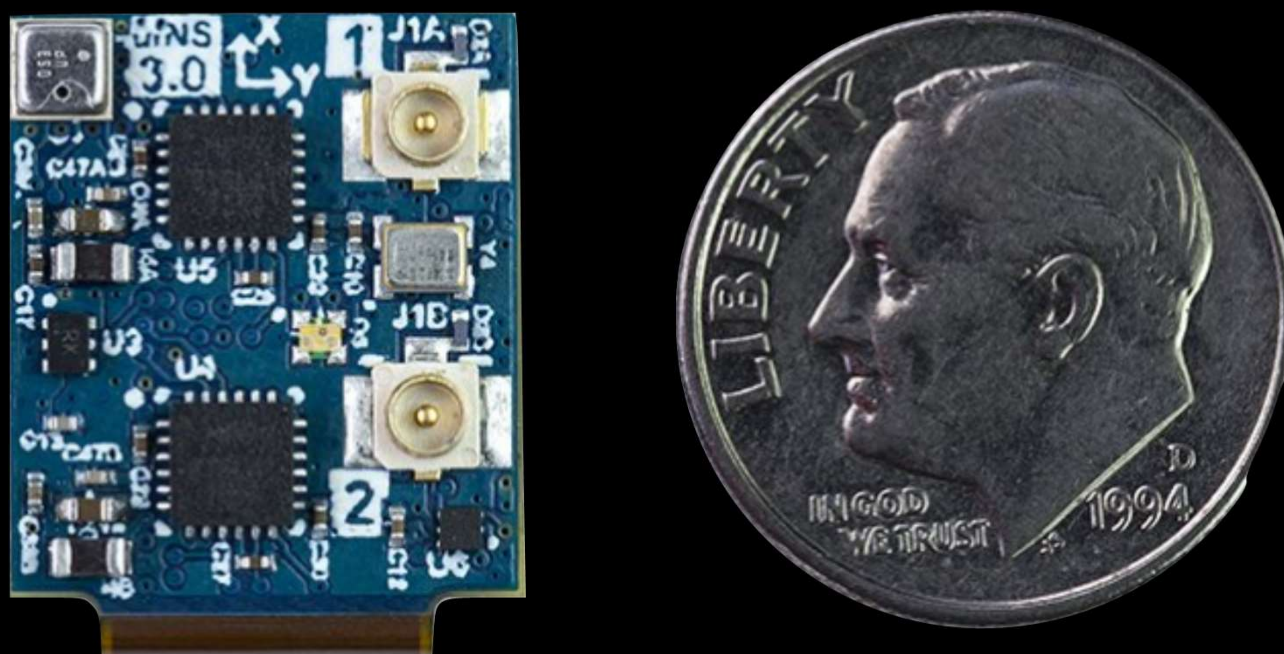
RONIN

Robust Neural Inertial Navigation in the Wild [ICRA 2020]

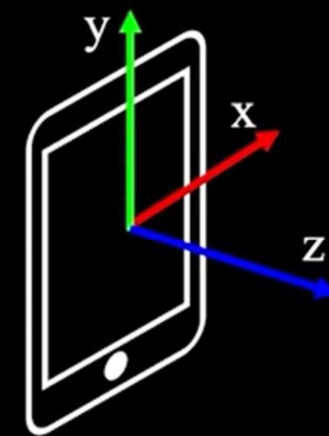
3. Our solution

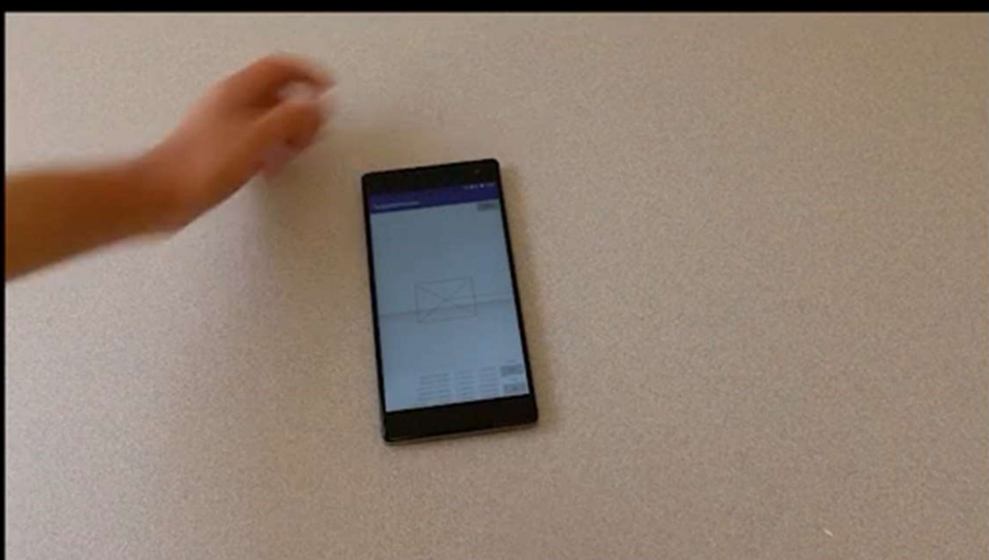
Inertial Measurement Unit (IMU)

(gyroscope, accelerometer, compass)



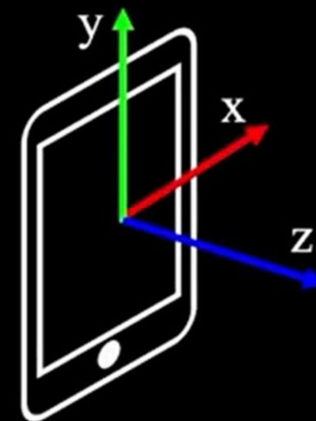
Gyroscope

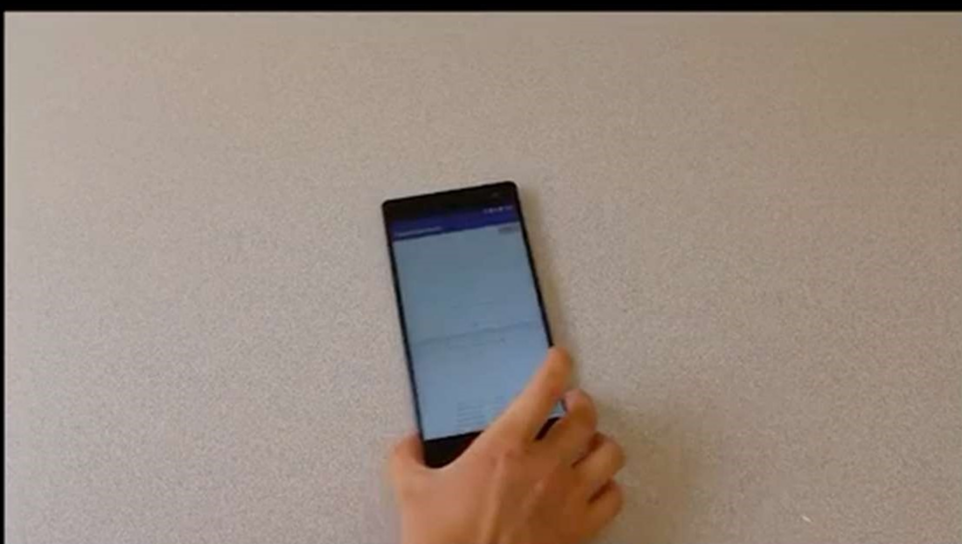




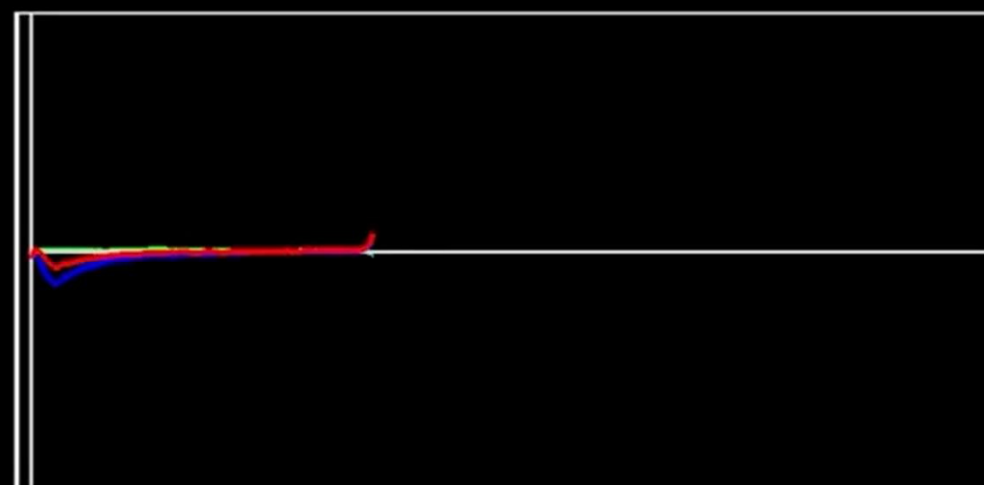
Angular velociy

Accelerometer



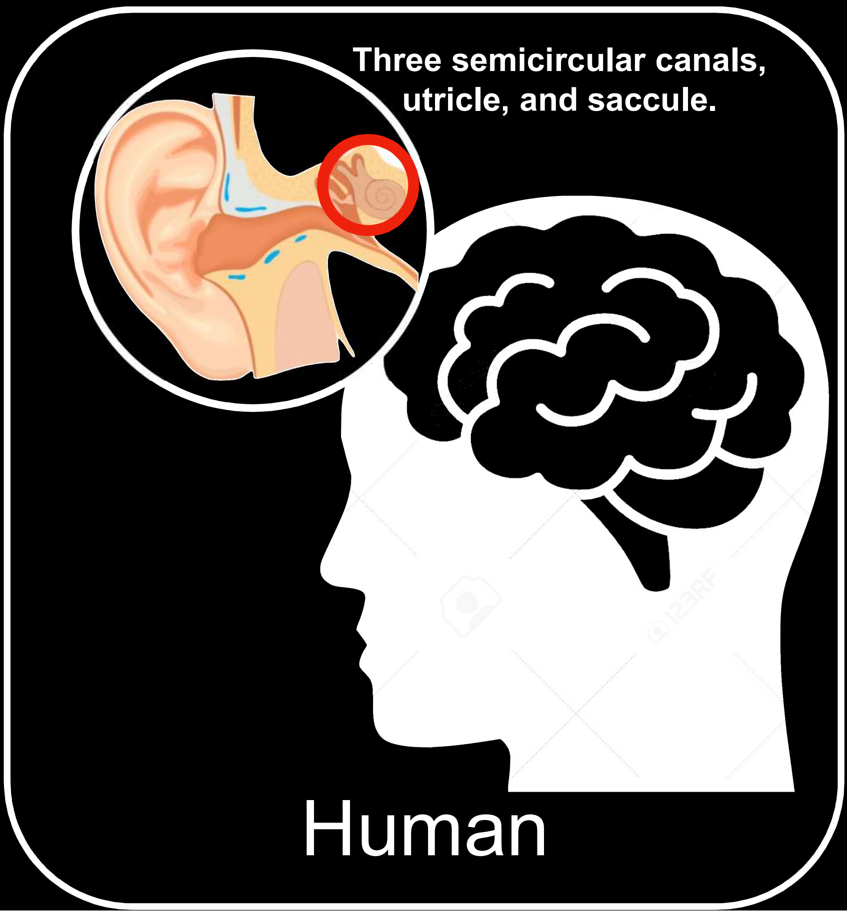


Linear acceleration



Computer vs. Human

vs.



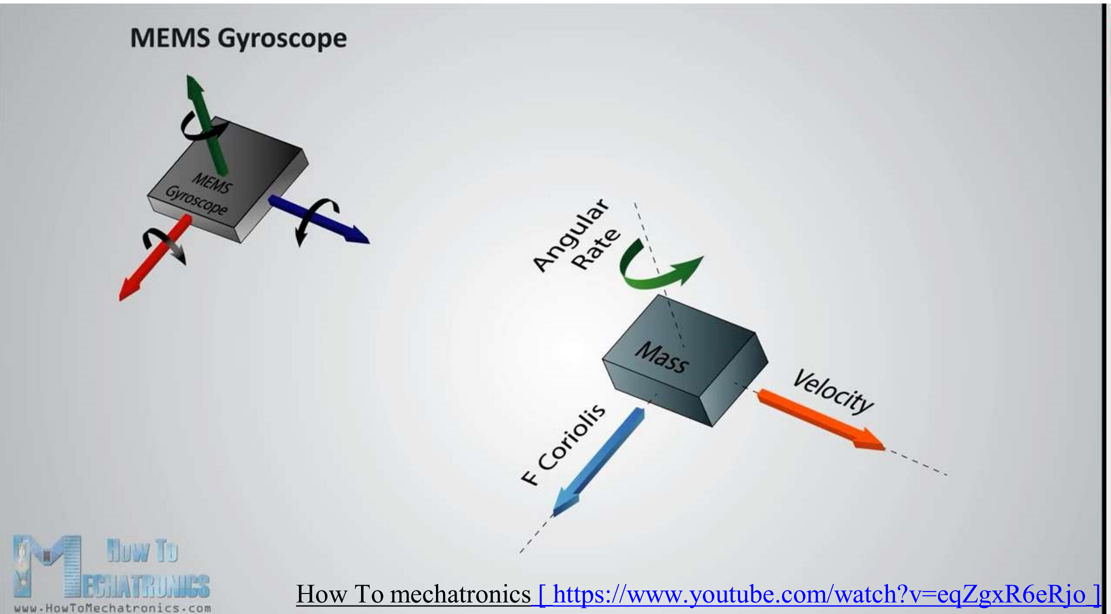
Computer vs. Human

Orientations

[https://www.youtube.com/watch?v=DthY8EBkb0o]

Positions

https://www.youtube.com/watch?v=5rwzbTSlgqY&t=147s



How To mechatronics [https://www.youtube.com/watch?v=eqZgxR6eRjo]

2013
08.03

ゴルゴ13に学ぶ「超長距離狙撃におけるコリオリ力の影響」

B! 4 ツイート Like 36

世界最高のスナイパー（狙撃者）といえば、それはもちろん、「ゴルゴ13」ことデューク東郷です。何しろ、常人どころか世界中の誰にだって不可能に思える狙撃を、数限りなく成功させているのです。

たとえば、右のシーンは、遙か先、狙撃ターゲットの屋敷にあるプールに生じる波の動きを読み、波の先に弾を反射（跳弾）させて、狙撃ターゲットに命中させた、という話です。こんな不可能を可能にすることができる存在は、ゴルゴ１３以外にはありえないでしょう。

このゴルゴ１３、地球が自転することで生じる「コリオリの力」も計算に入れた上で、狙撃を行うと言われています*。地球自転によるコリオリ力というのは、赤道に近いほど（地球自転による）回転周速度が速いことから（北極・南極では周速度ゼロ）、緯度方向に移動する物体が軽度方向に対する力を受ける、というものです。 ゴルゴは、狙撃を行う際に、周りの風や重力が弾丸に対して働く影響を考えるなんて「当たり前」、地球の自転により生じる「弾丸曲がり」の補正まで行っているというのです。そこで、今回はゴルゴ13が行う超長距離狙撃に対する「コリオリ力の影響」を考えてみることにします。

中でも私にとって印象に残っているのは、南半球から来た暗殺者と闘うストーリーの中でコリオリの力を計算に入れて狙撃することである。

ゴルゴ13は「プロフェッショナル」と呼べるのか

ゴルゴ１３は、おおよそ1km程度離れたところからの長距離狙撃を成功させます。その1km程度の狙撃を行う際、ライフルから発射される弾丸に重力とコリオリ力のみが働くとして（つまり空気抵抗を無視して）、弾丸の軌道がどのように曲がってしまうかを計算してみた結果が、下のグラフです。 ゴルゴ１３が発射する弾丸の初速度は995m/sとして、左図が東京で真北を向いて狙撃を行った場合で、右図が赤道から真北を向いて狙撃した場合です（軸の単位はすべてメートルです）。グラフに描いた実線が銃弾にコリオリ力が働いた銃弾の軌跡で、点線がコリオリ力を無視した銃弾の軌跡です。

このグラフを眺めると、銃弾が南北方向に1000メートル進む間に、鉛直方向に対して５メートル落ち、そしてコリオリ力により、東京では0.8メートル・

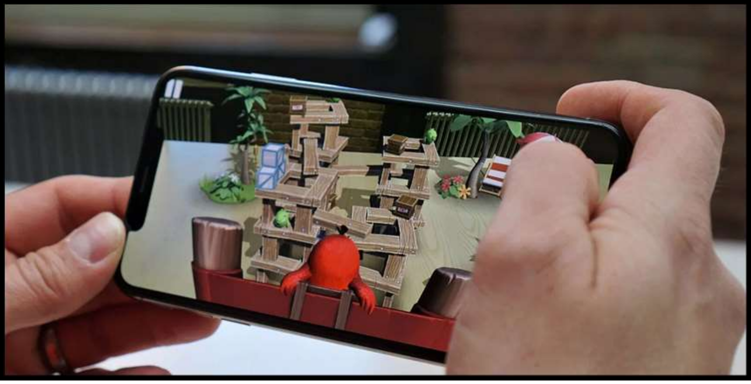
Inertial Measurement Unit (IMU)

Activity recognition

VR: Orientation tracking

Body motion capture

AR: Position estimation (supplement)



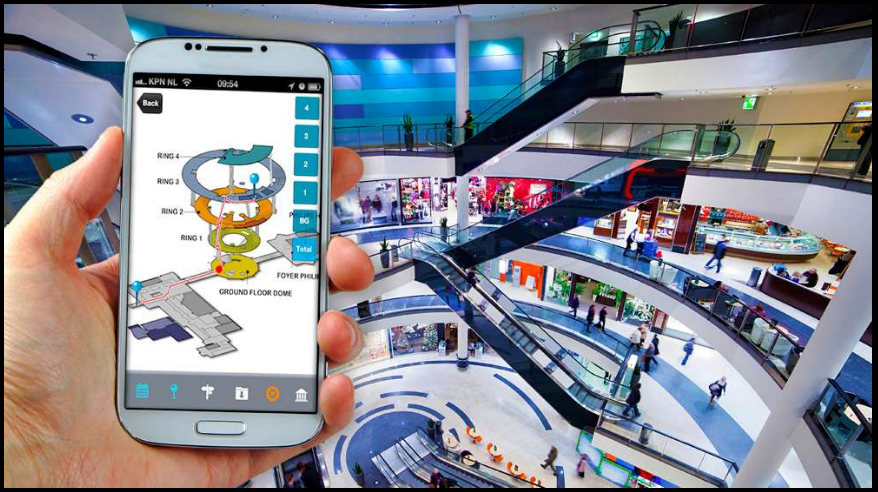
Inertial Navigation

Why use motion sensing?

Where am I?

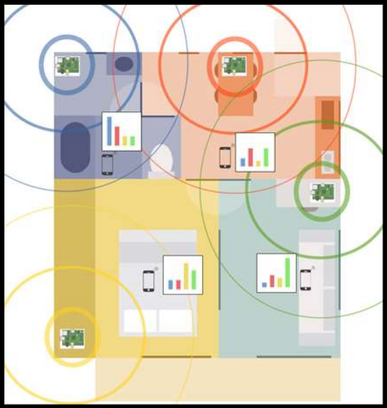
=

Computer

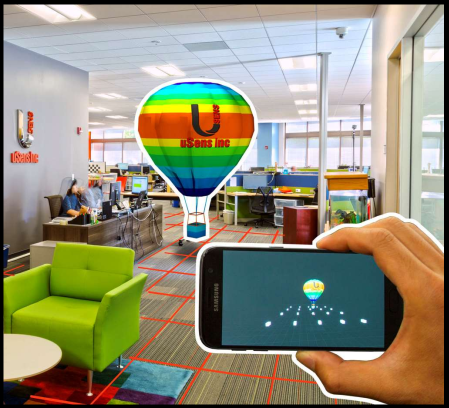


Mobile computing

GPS



Wireless (RSSI, RTT, 5G)



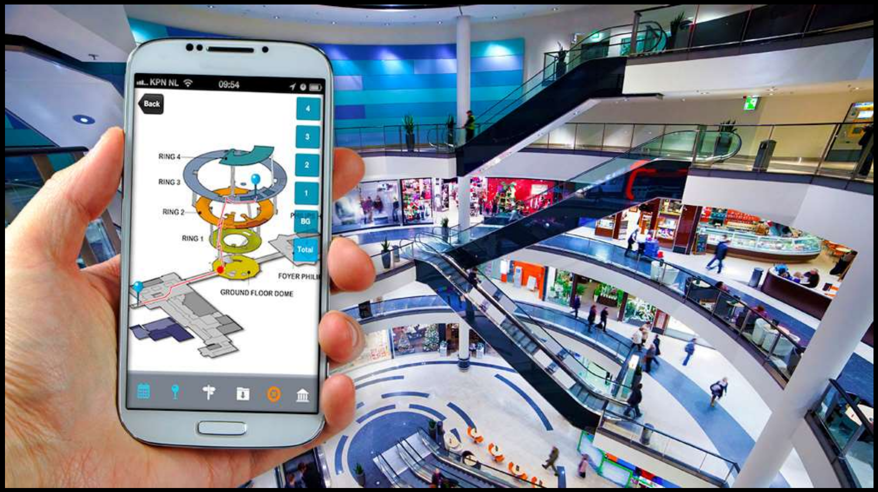
Camera

Where am I?

=

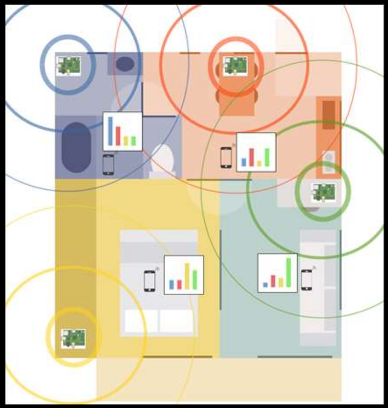
Computer

Indoor

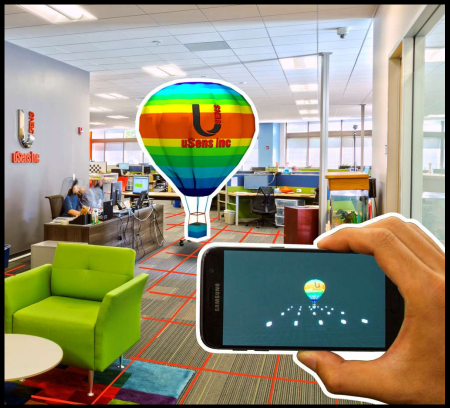


Mobile computing

GPS



Wireless (RSSI, RTT, 5G)



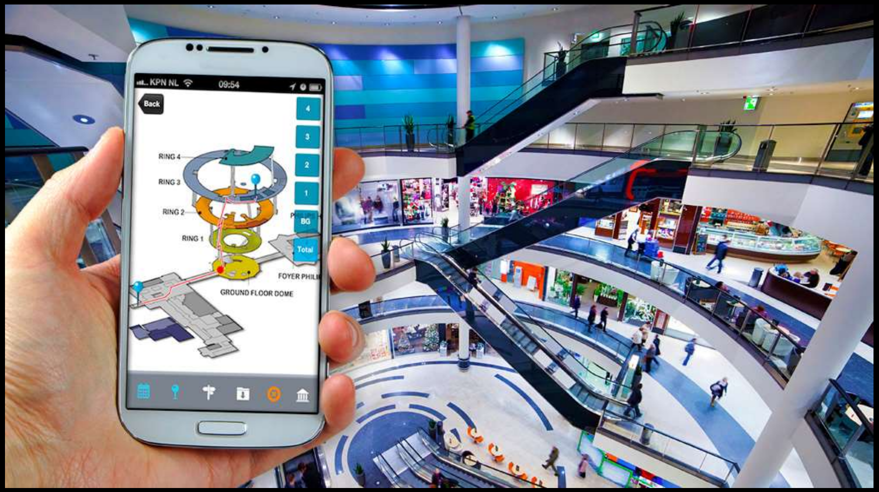
Camera

Where am I?

||

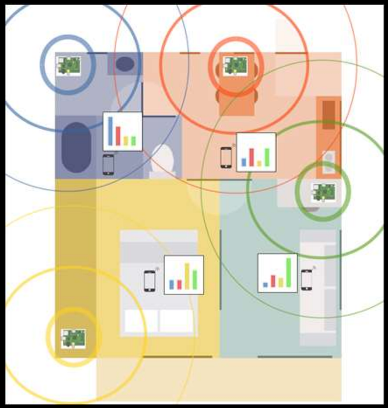
Computer

Indoor **Anytime/Anywhere**

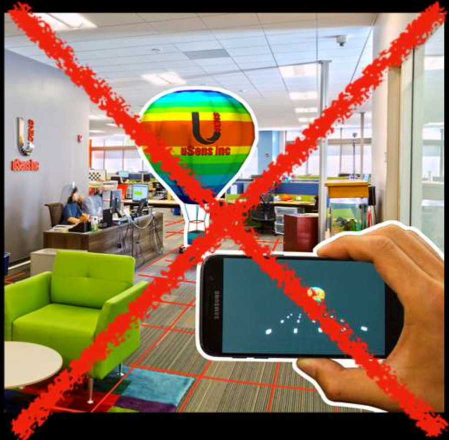


Mobile computing

GPS



Wireless (RSSI, RTT, 5G)



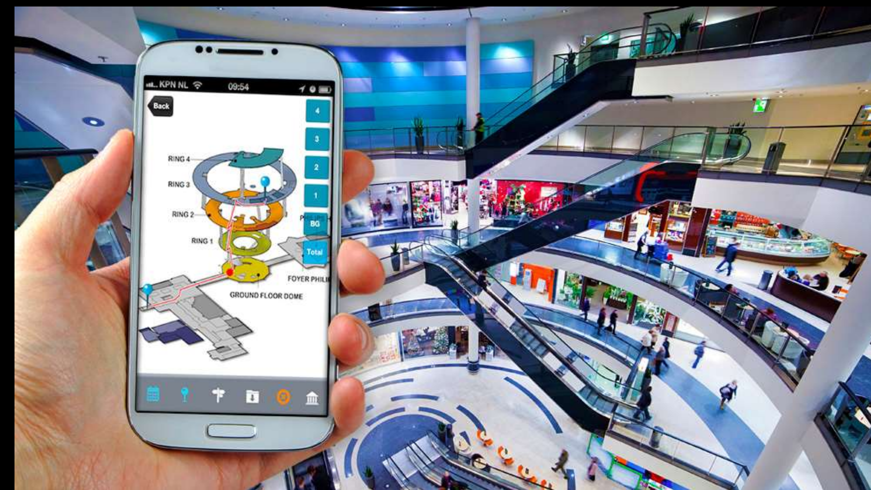
Camera

Where am I?

=

Computer

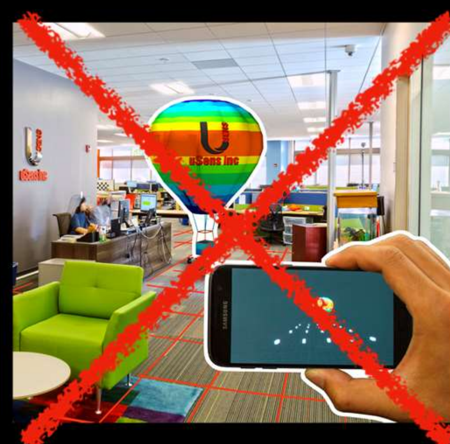
Indoor **Anytime/Anywhere**



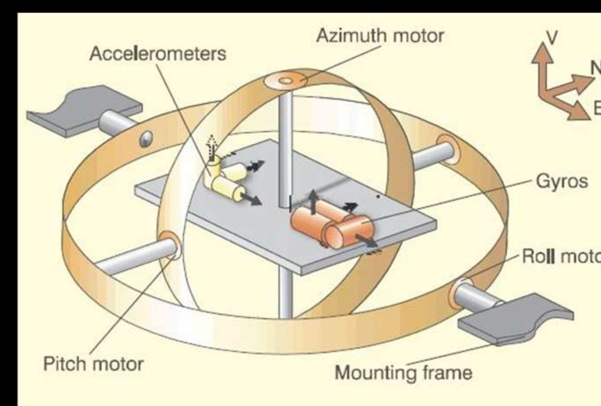
Mobile computing

GPS

Wireless (RSSI, RTT, 5G)



Camera



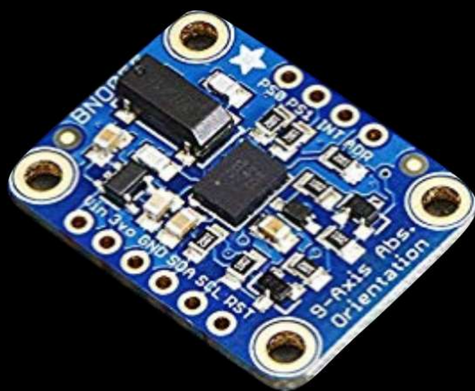
Motion sensor (IMU)
[image from IEEE GlobalSpec]

Inertial navigation = Ultimate anytime anywhere navigation

Energy efficient

Indoors

Inside pocket



1. What is IMU?

2. Existing approach

RONIN

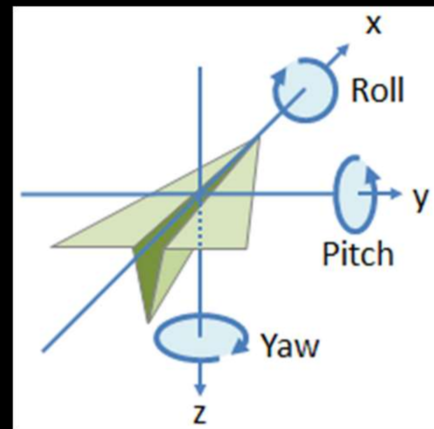
Robust Neural Inertial Navigation in the Wild [ICRA 2020]

3. Our solution

Existing approaches
(inertial navigation, dead reckoning)

Motion sensors → **Orientations** / **Positions**

Device orientation (Kalman Filter)



IMU

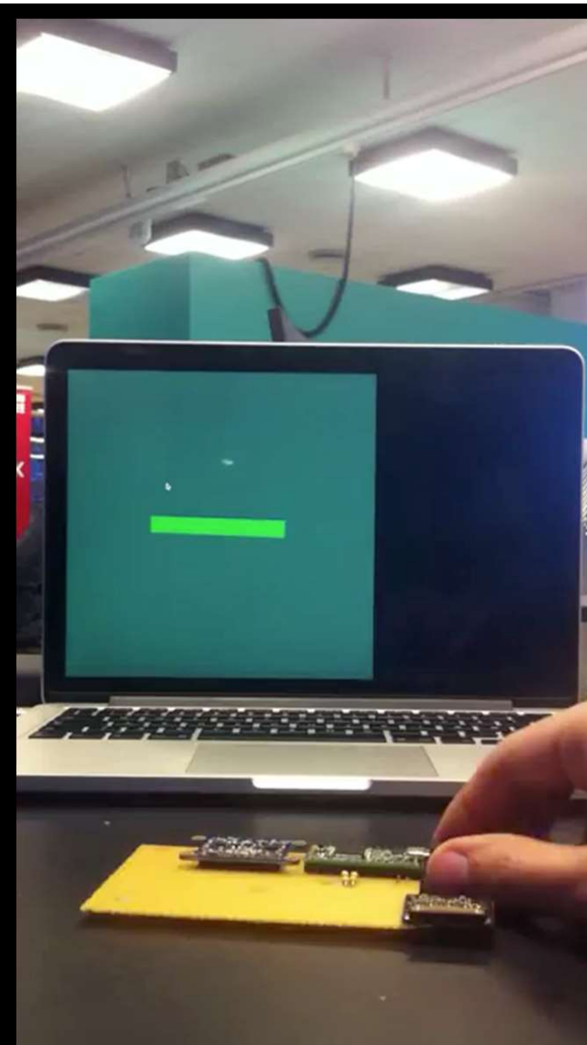
Angular velocity (gyroscope)

Acceleration + gravity (accelerometer)

Magnetic field (compass)

Kalman Filter

Roll
Pitch
Yaw



Daniel Safari
https://www.youtube.com/watch?v=82_5yagSaUM

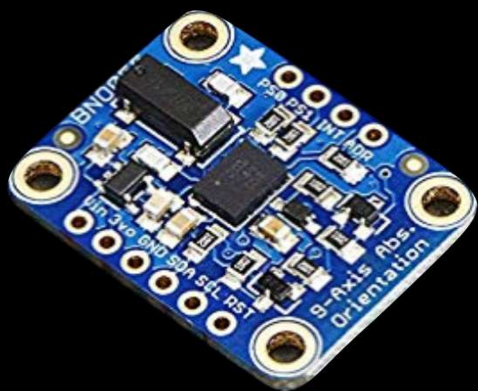
Position Estimation

Existing approach

- Device orientations (Kalman Filter)
- Assume
  - A phone faces forward
  - Moves forward
  - Step counting works

[Pession, Wac, and Konstantas: WayFiS]

Human activities in the wild



1. What is IMU?

2. Existing approach

RONIN

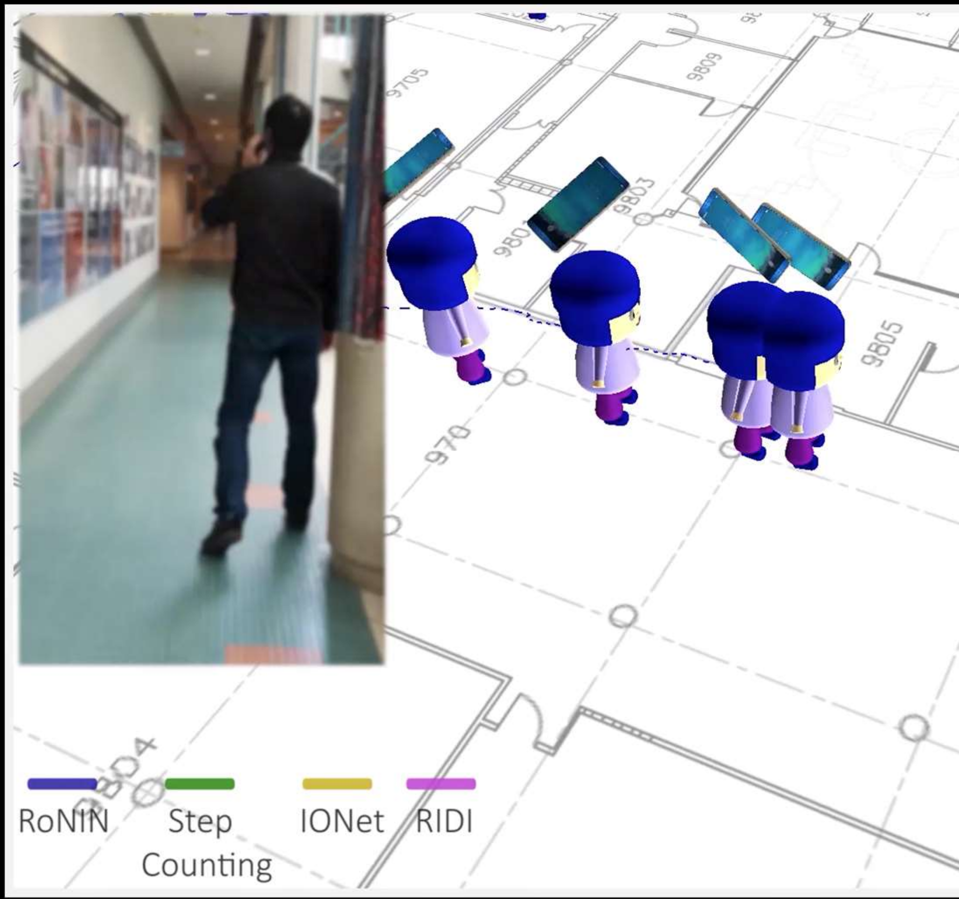
Robust Neural Inertial Navigation in the Wild [ICRA 2020]

3. Our solution

43 hours
30 million frames
100 kilometers
100 humans
3 buildings
4 phones

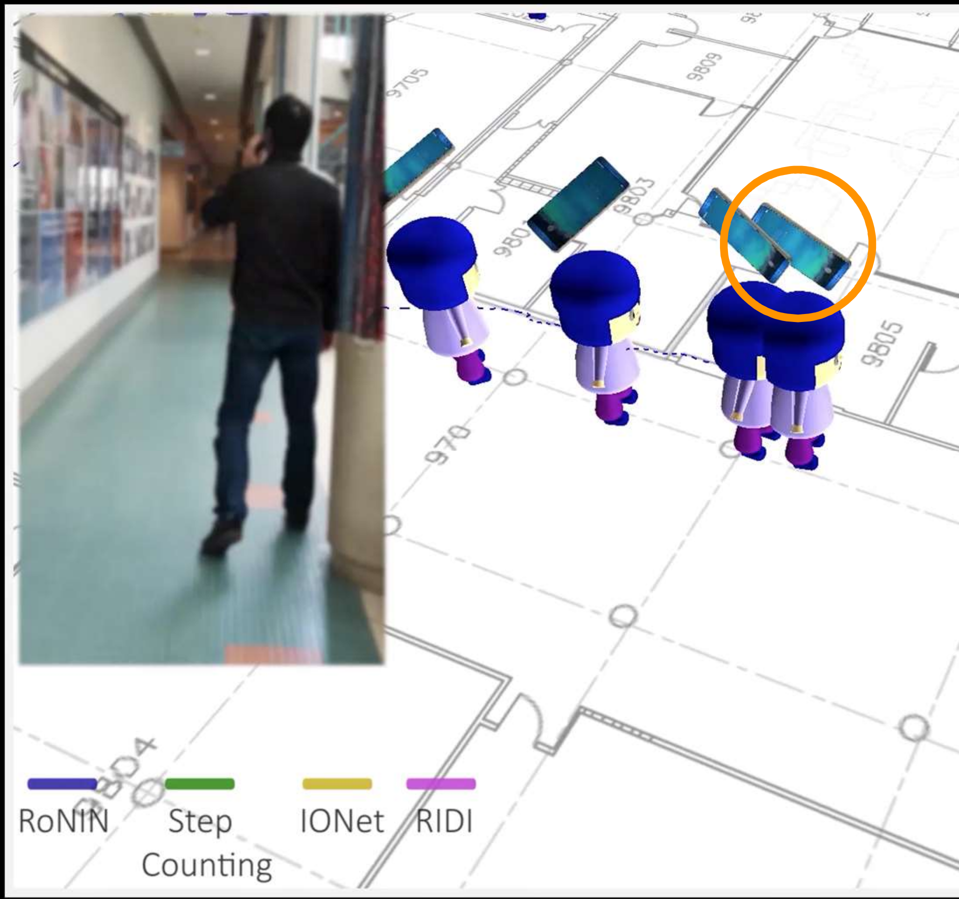
Robust Neural Inertial Navigation (RONIN)

- Device orientations
- Body positions



Robust Neural Inertial Navigation (RONIN)

- Device orientations by Kalman Filter
- Body positions

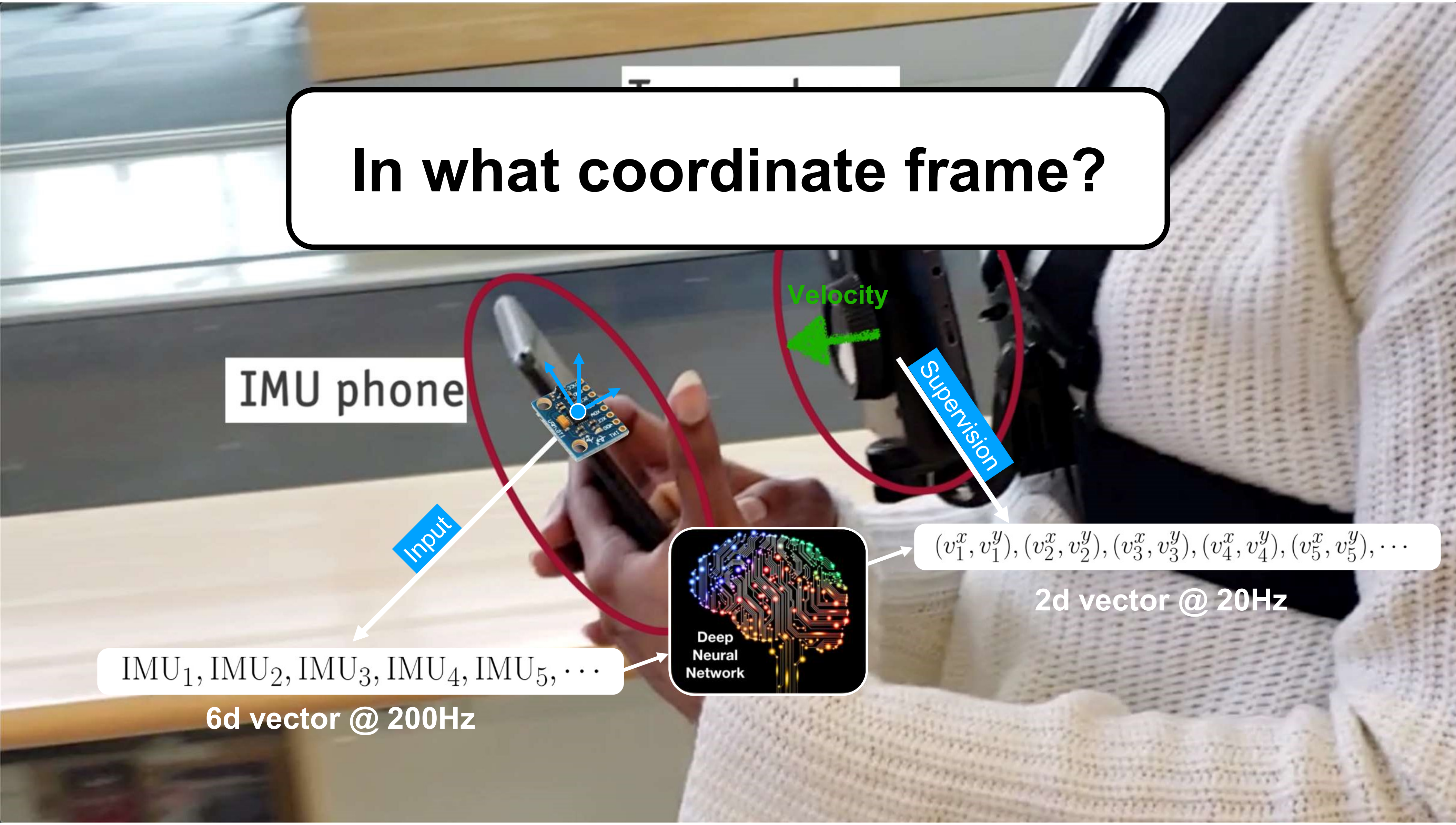


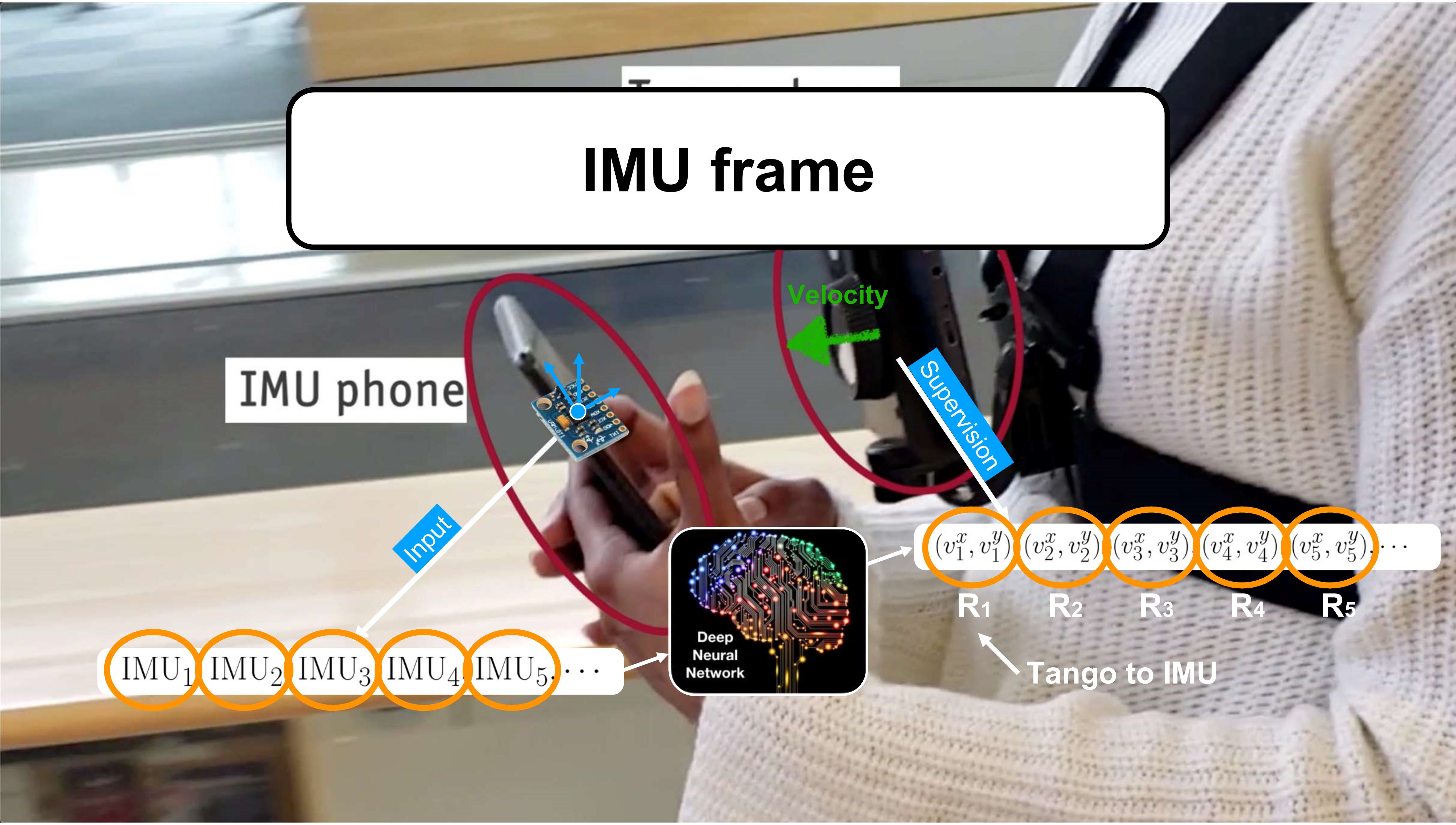
Robust Neural Inertial Navigation (RoNIN)

- Device orientations by Kalman Filter
- Body position derivatives (velocities) by Deep Learning

Tango phone
Velocity
IMU phone
Supervision
Input
$(v_1^x, v_1^y), (v_2^x, v_2^y), (v_3^x, v_3^y), (v_4^x, v_4^y), (v_5^x, v_5^y), \cdots$
2d vector @ 20Hz
Deep
Neural
Network
$\mathrm{IMU}_1, \mathrm{IMU}_2, \mathrm{IMU}_3, \mathrm{IMU}_4, \mathrm{IMU}_5, \cdots$
6d vector @ 200Hz

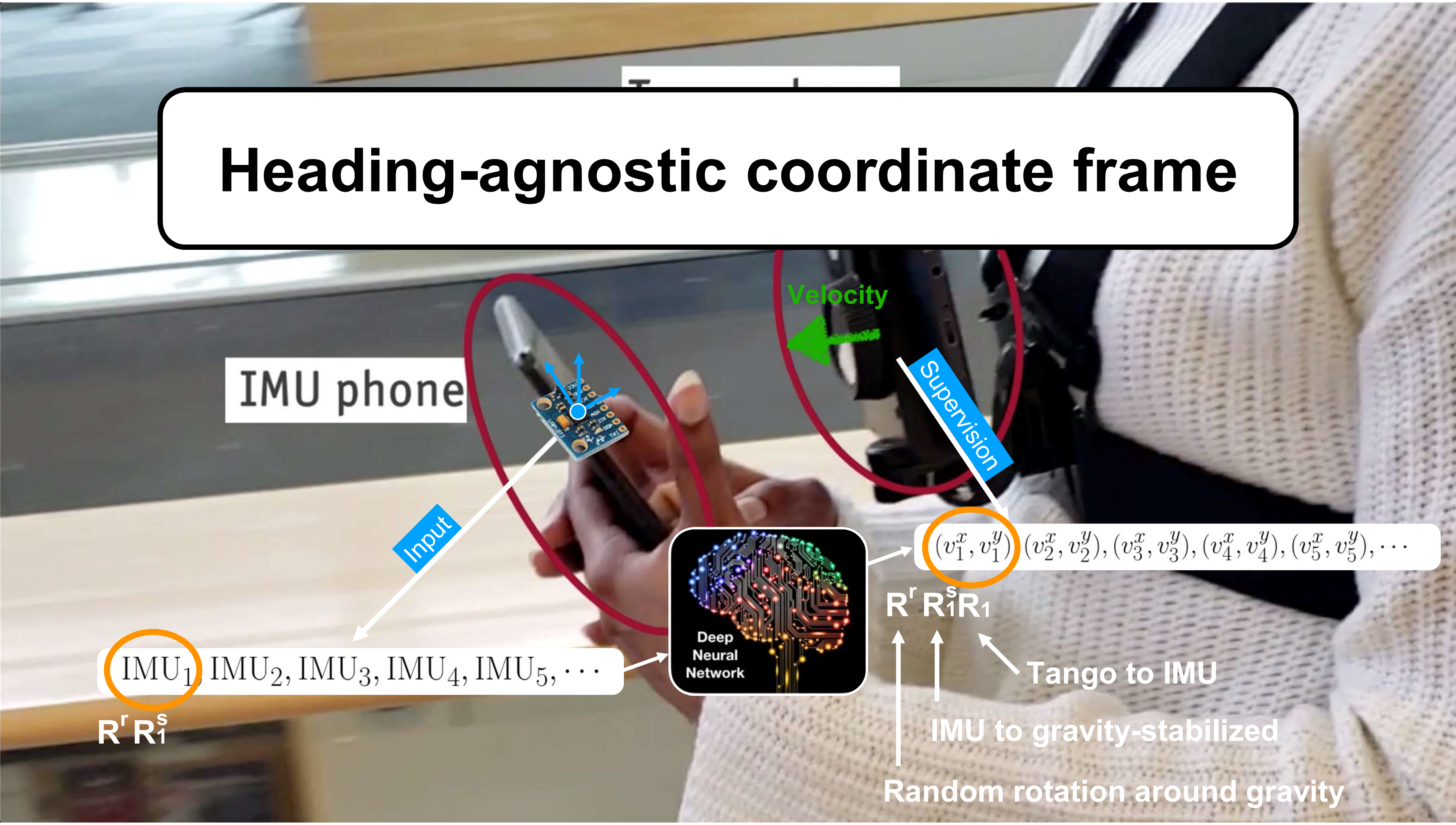
In what coordinate frame?



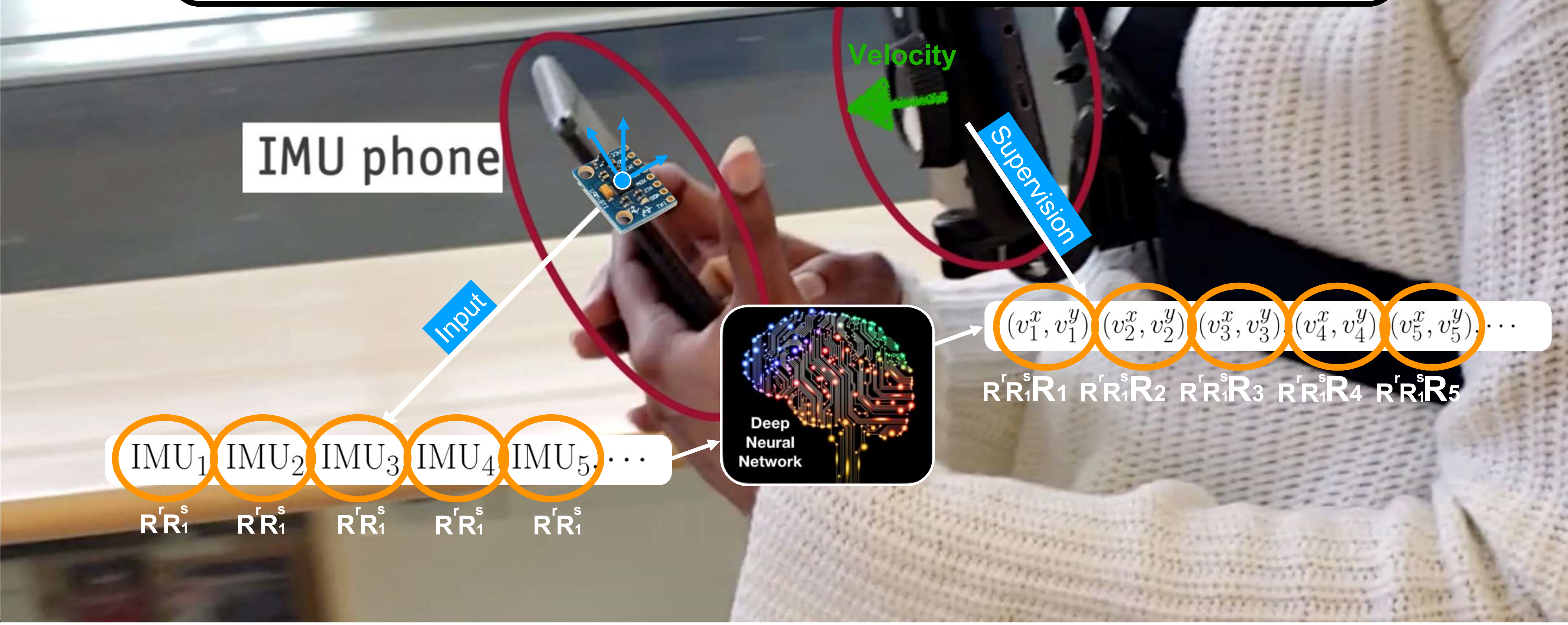


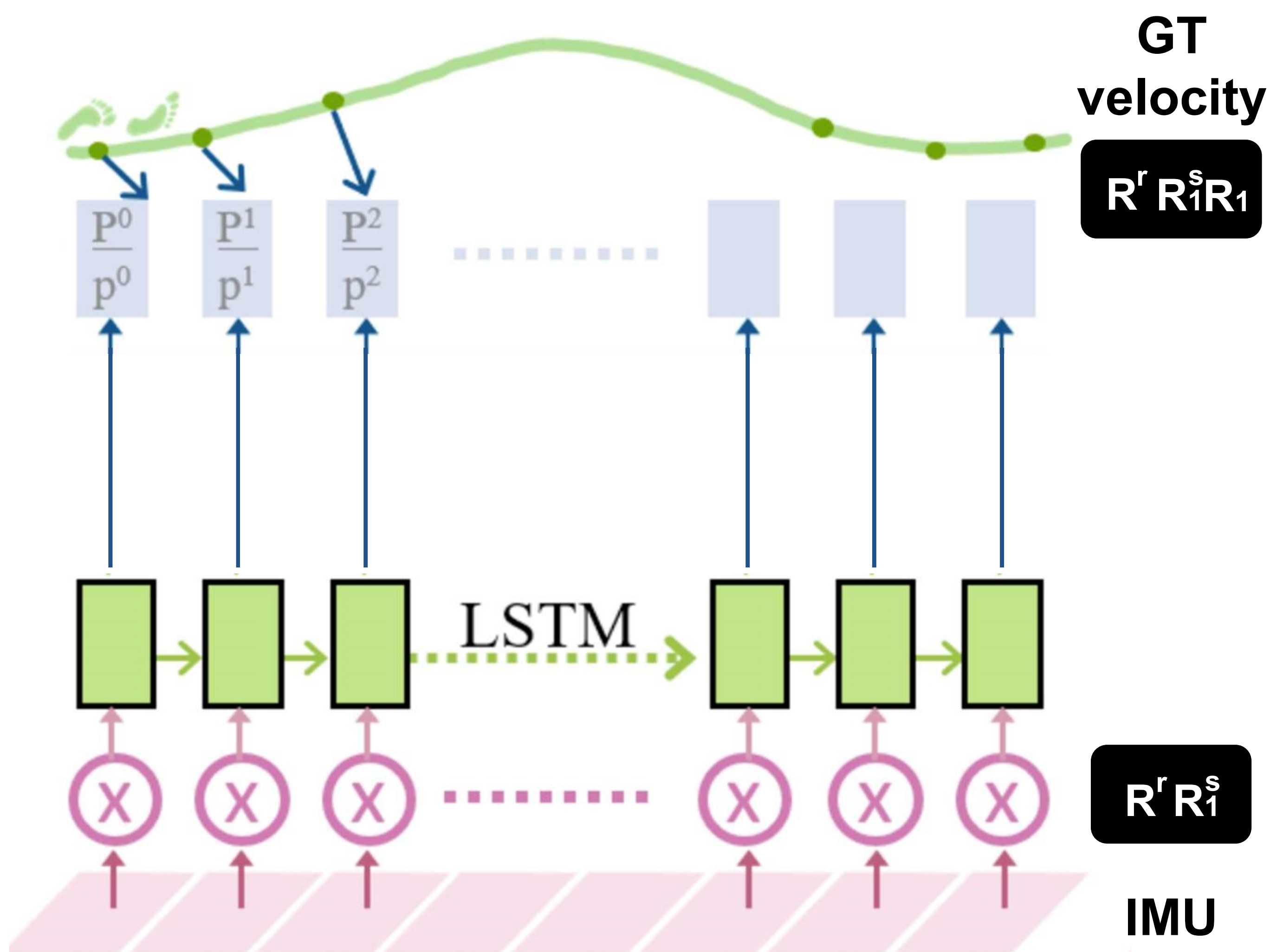
IMU frame
IMU phone
Velocity
Supervision
Input
$\mathrm{IMU}_1\ \mathrm{IMU}_2\ \mathrm{IMU}_3\ \mathrm{IMU}_4\ \mathrm{IMU}_5 \cdots$
Deep
Neural
Network
$(v_1^x, v_1^y)\ (v_2^x, v_2^y)\ (v_3^x, v_3^y)\ (v_4^x, v_4^y)\ (v_5^x, v_5^y) \cdots$
R_1 R_2 R_3 R_4 R_5
Tango to IMU

Heading-agnostic coordinate frame

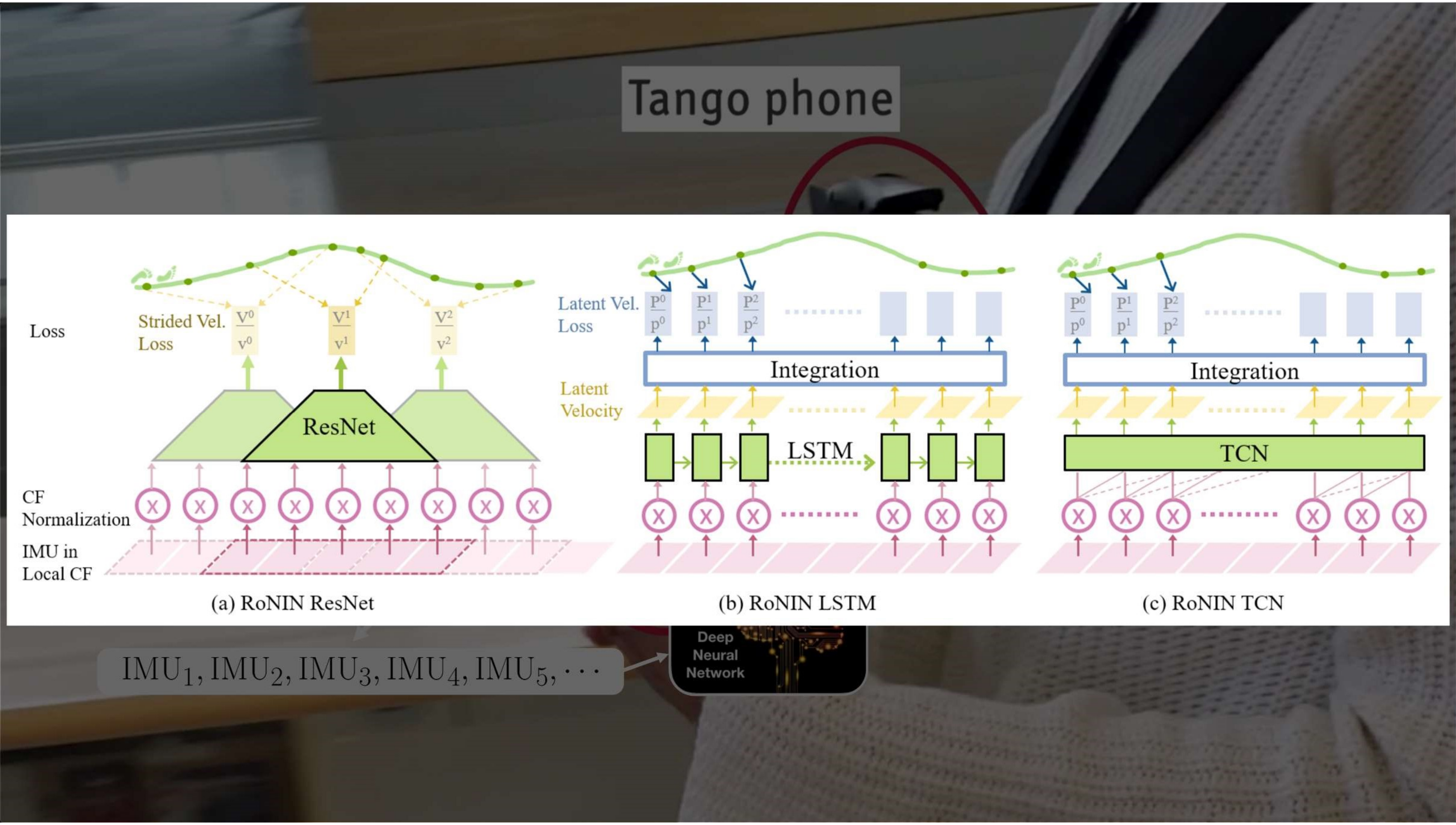


Heading-agnostic coordinate frame



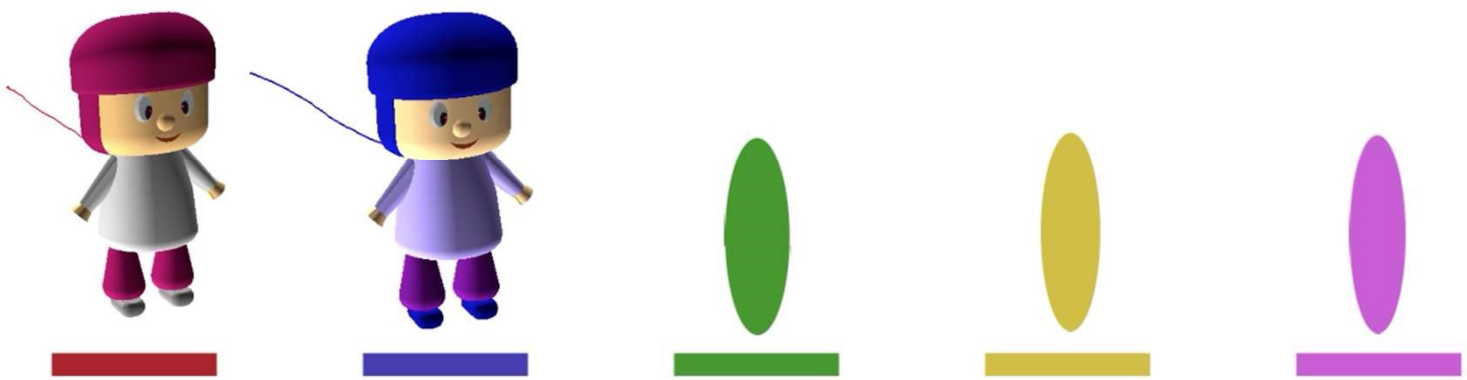


(b) RoNIN LSTM



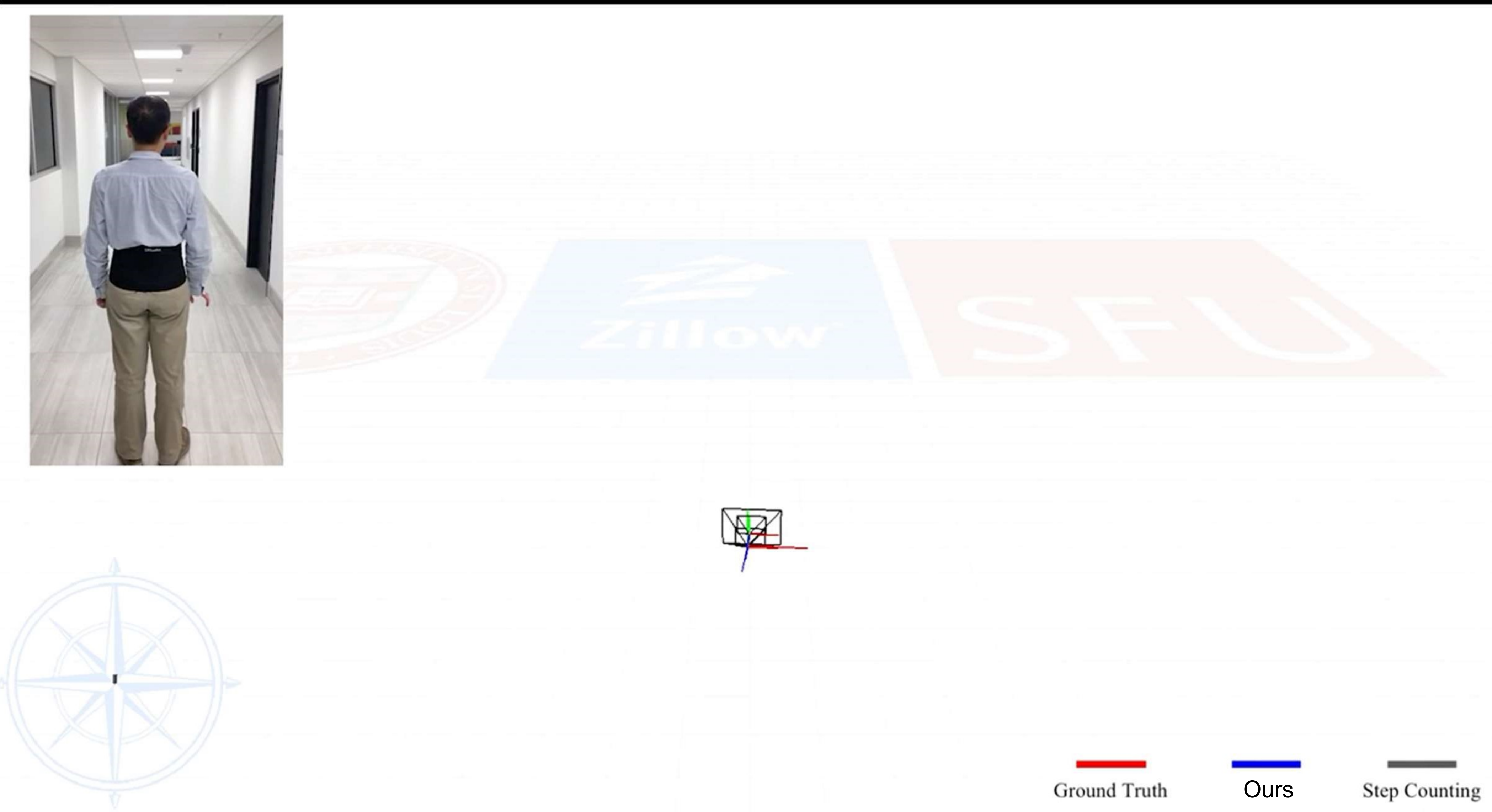
(a) RoNIN ResNet (b) RoNIN LSTM (c) RoNIN TCN

Trajectory Viewer



Ground Truth RoNIN Step Counting IONet[1] RIDI[2]

[1] C. Chen, X. Lu, A. Markham, and N. Trigoni. IONet: Learning to cure the curse of drift in inertial odometry. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018
[2] H. Yan, Q. Shan, and Y. Furukawa. Ridi: Robust IMU double integration. In Proceedings of the European Conference on Computer Vision (ECCV), 2018


Ground Truth
Ours
Step Counting


6x
RoNIN
Step Counting
IONet
RIDI

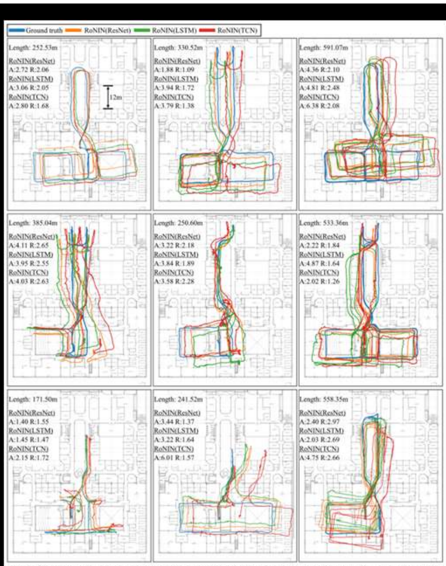


Figure 2. Selected visualizations of trajectories from 3 variants of RoNIN method on our dataset. Positional errors are marked within each figure, where "A" denotes ATE and "R" denotes RTE.

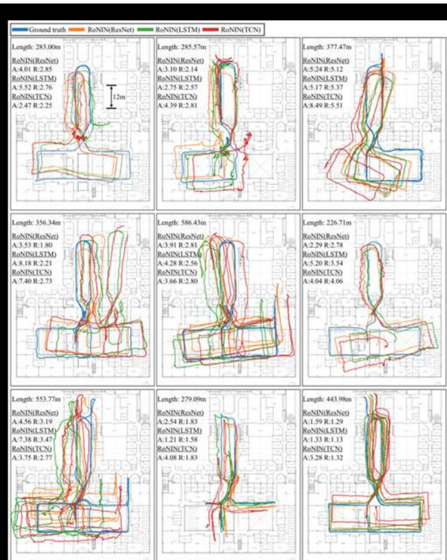


Figure 3. Selected visualizations of trajectories from 3 variants of RoNIN method on our dataset. Positional errors are marked within each figure, where "A" denotes ATE and "R" denotes RTE.

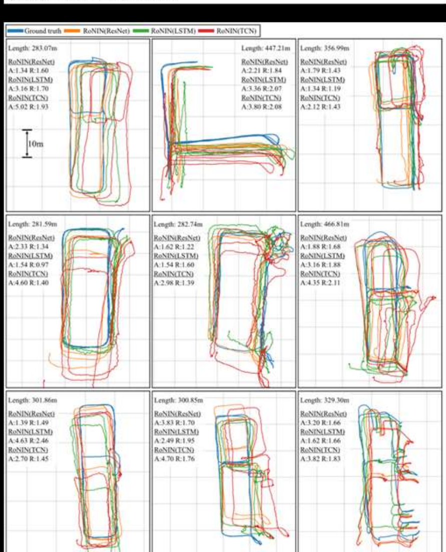


Figure 4. Selected visualizations of trajectories from 3 variants of RoNIN method on our dataset. Positional errors are marked within each figure, where "A" denotes ATE and "R" denotes RTE.

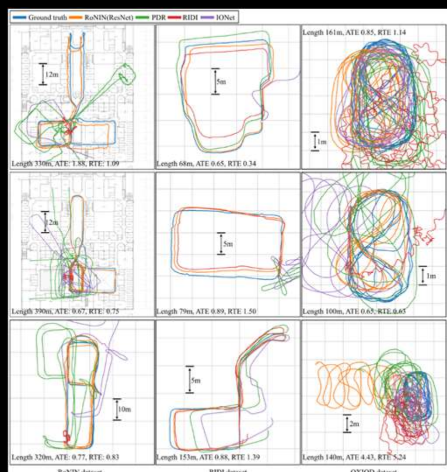
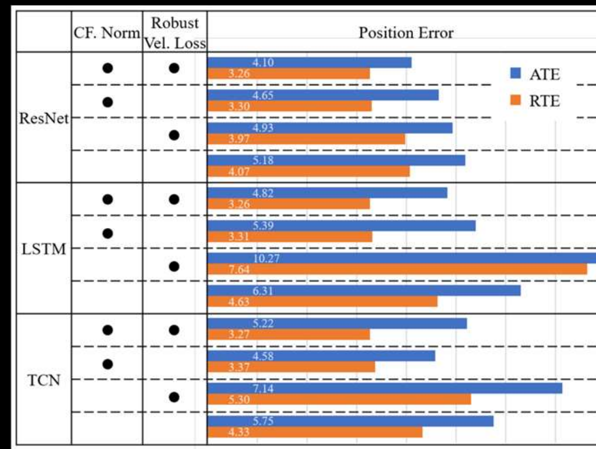
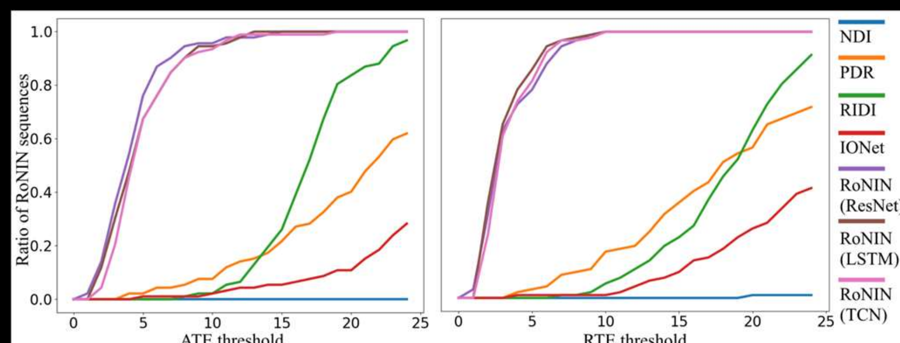
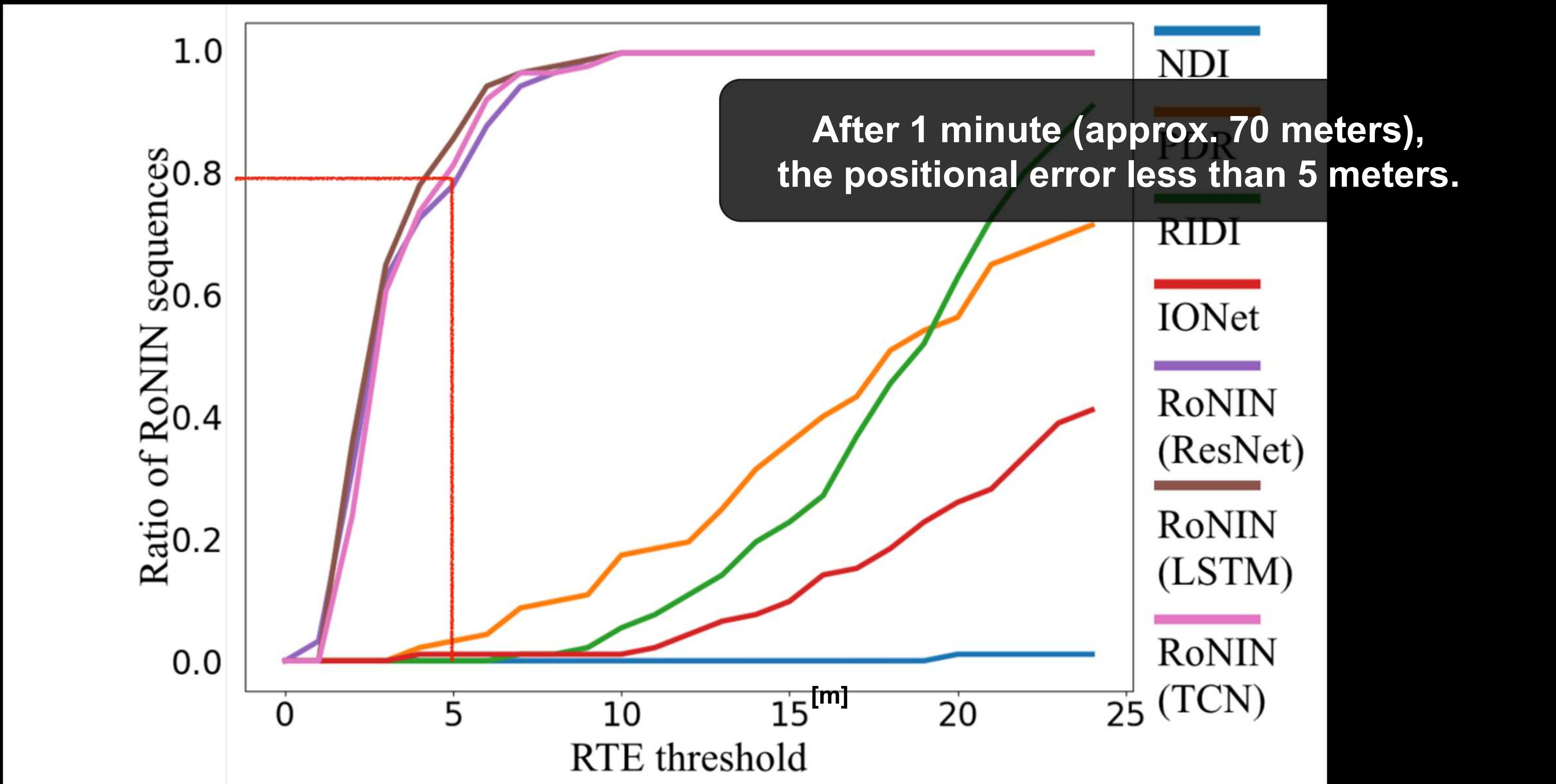


Figure 4. Selected visualizations. We select 3 examples from each dataset and visualize reconstructed trajectories from all competing methods. We choose RoNIN ResNet as our method, since its performance is more consistent across datasets. For each sequence we mark the trajectory length and report both ATE and RTE of our method. We also mark physical dimensions in all sequences to demonstrate that our method estimate trajectories with accurate scales. Three examples from our RoNIN dataset (left column) contains complex natural motions, where all other methods fail. Sequences from the RIDI dataset (middle column) contains hard motions. In particular, the middle example of the middle column contains extensive backward motion, where our method handles elegantly. Sequences from the OXIOD dataset (right column) are mostly short sequences with easy motions. However, our method gives large error for a few sequences (e.g. the bottom one) due to the large error in the provided device orientations.

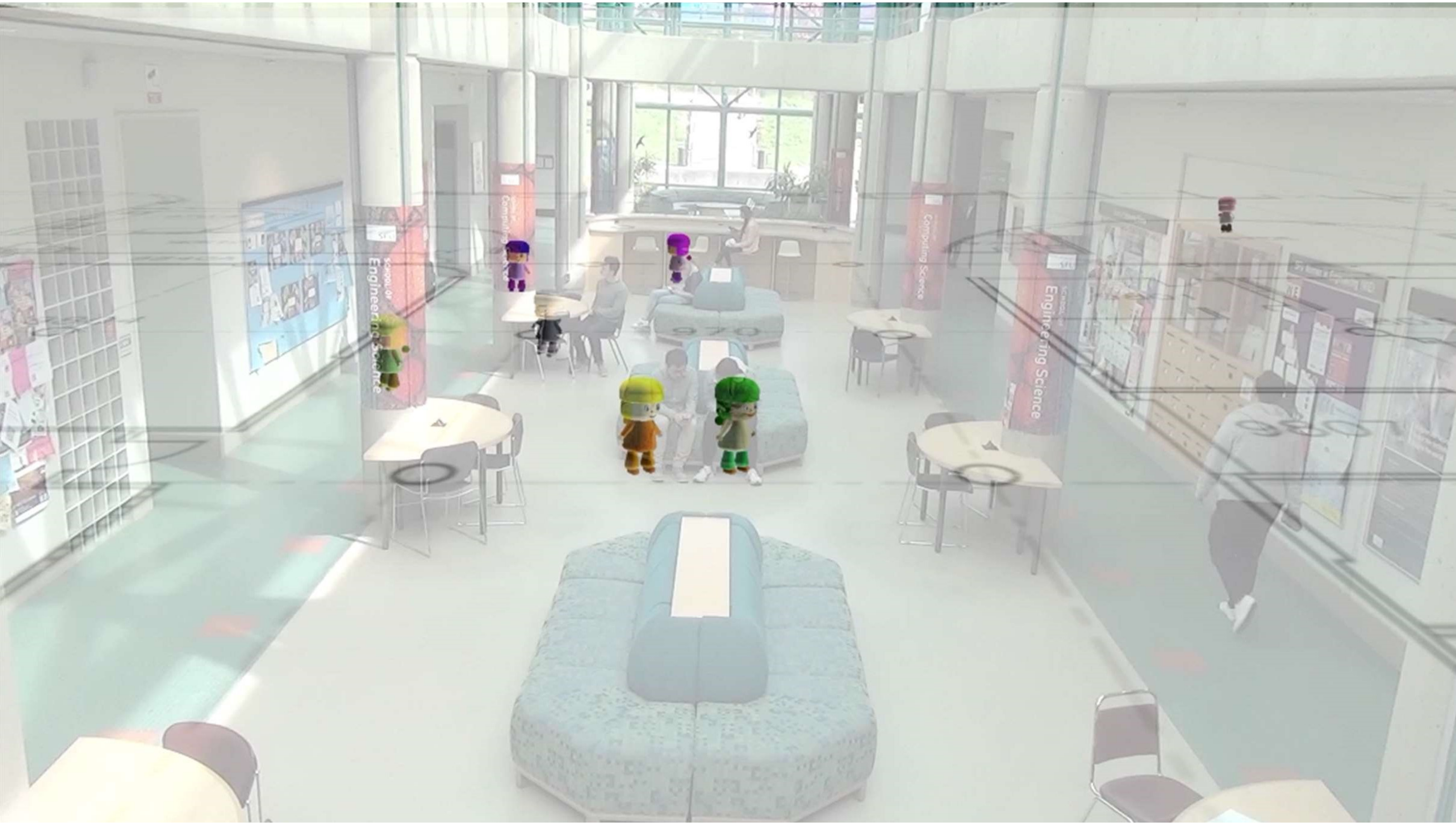


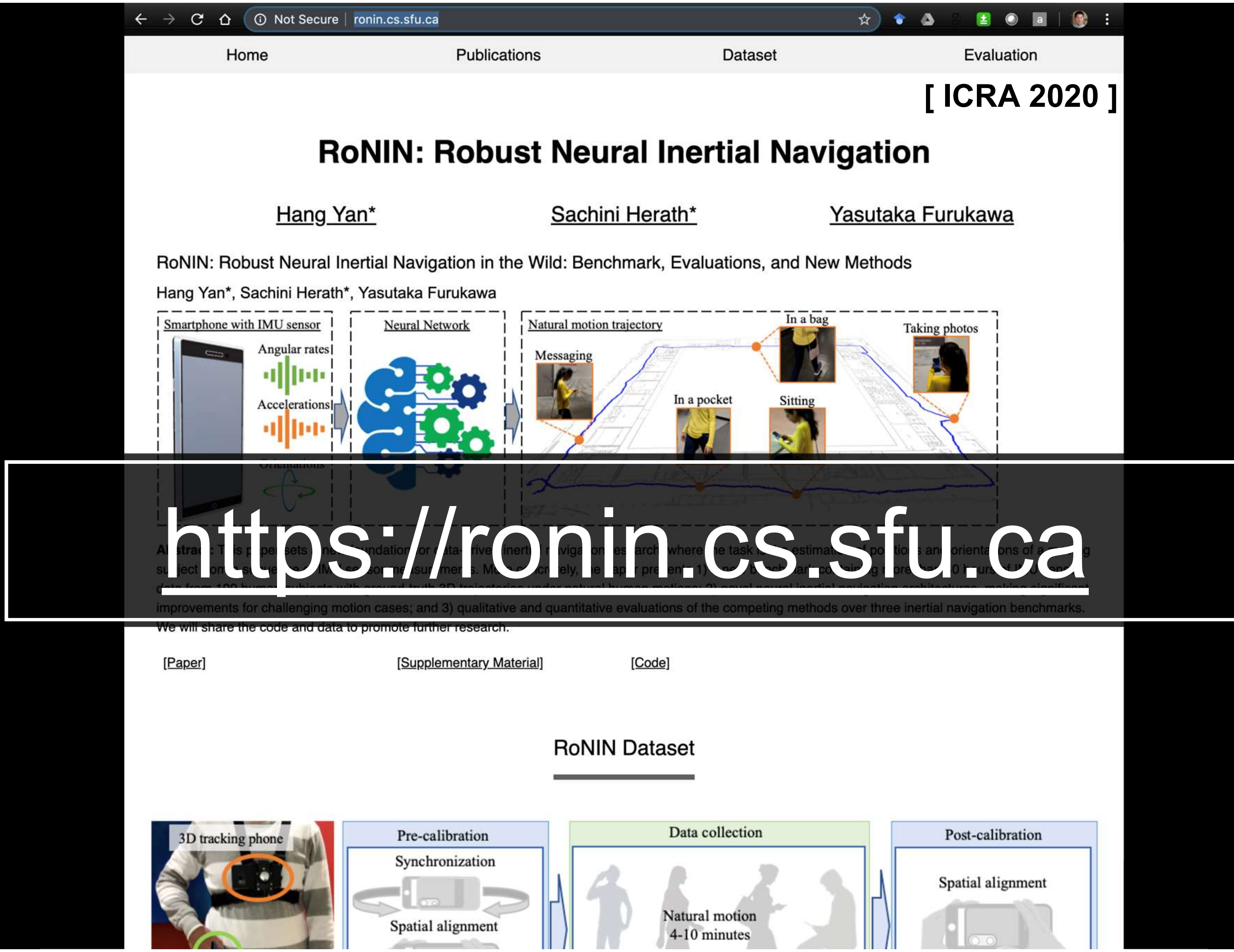
	Test subjects	Metric	NDI	PDR	RIDI	IONet	RoNIN ResNset	RoNIN LSTM	RoNIN TCN
RIDI Dataset	Seen	ATE	31.06	3.52	1.88	11.46	1.63	2.00	1.66
		RTE	37.53	4.56	2.38	14.22	1.91	2.64	2.16
	Unseen	ATE	32.01	1.94	1.71	12.50	1.67	2.08	1.66
		RTE	38.04	1.81	1.79	13.38	1.62	2.10	2.26
OXIOD Dataset	Seen	ATE	716.31	2.12	4.12	1.79	2.40	2.02	2.26
		RTE	606.75	2.11	3.45	1.97	1.77	2.33	2.63
	Unseen	ATE	1941.41	3.26	4.50	2.63	6.71	7.12	7.76
		RTE	848.55	2.32	2.70	2.63	3.04	5.42	5.78
RoNIN Dataset	Seen	ATE	675.21	29.54	17.06	31.07	3.54	4.18	4.38
		RTE	169.48	21.36	17.50	24.61	2.67	2.63	2.90
	Unseen	ATE	458.06	27.67	15.66	32.03	5.14	5.32	5.70
		RTE	117.06	23.17	18.91	26.93	4.37	3.58	4.07





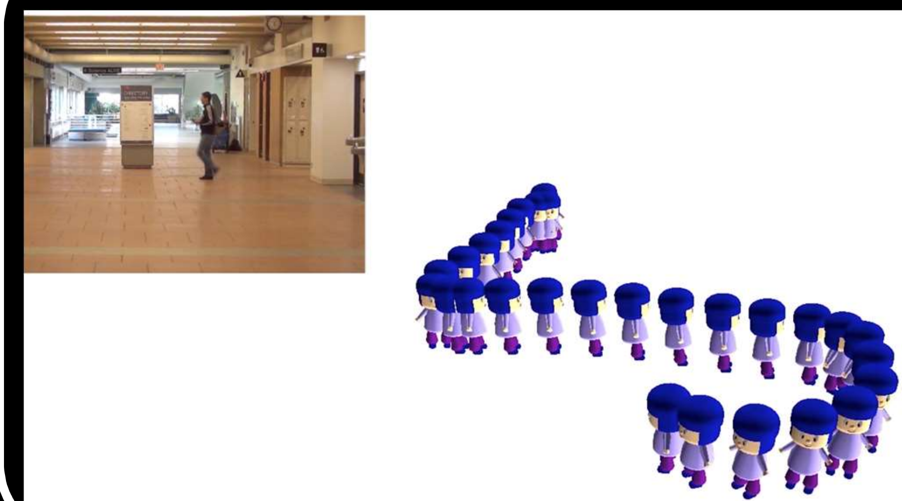
RTE: Relative Trajectory Error


Engineering Science
Computing Science

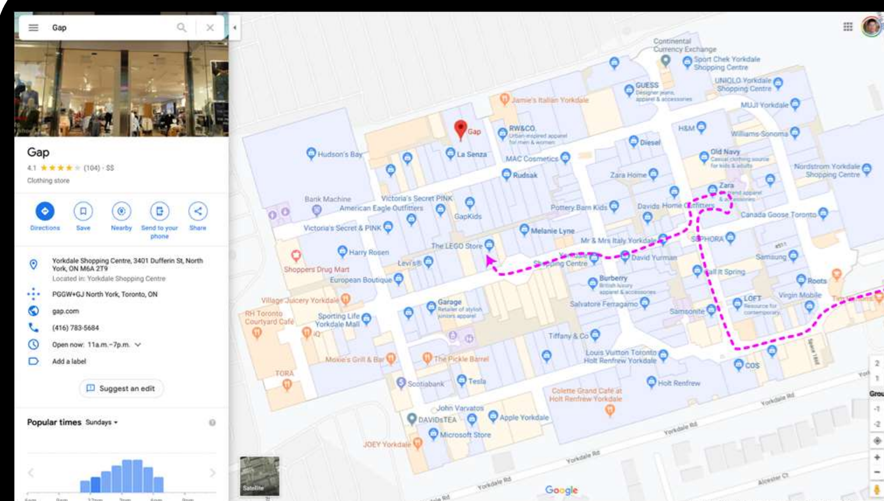

Not Secure | ronin.cs.sfu.ca
Home
Publications
Dataset
Evaluation
[ICRA 2020]
RoNIN: Robust Neural Inertial Navigation
Hang Yan*
Sachini Herath*
Yasutaka Furukawa
RoNIN: Robust Neural Inertial Navigation in the Wild: Benchmark, Evaluations, and New Methods
Hang Yan*, Sachini Herath*, Yasutaka Furukawa
Smartphone with IMU sensor
Angular rates
Accelerations
Neural Network
Natural motion trajectory
Messaging
In a bag
Taking photos
In a pocket
Sitting
https://ronin.cs.sfu.ca
improvements for challenging motion cases; and 3) qualitative and quantitative evaluations of the competing methods over three inertial navigation benchmarks.
We will share the code and data to promote further research.
[Paper]
[Supplementary Material]
[Code]
RoNIN Dataset
3D tracking phone
Pre-calibration
Synchronization
Spatial alignment
Data collection
Natural motion
4-10 minutes
Post-calibration
Spatial alignment

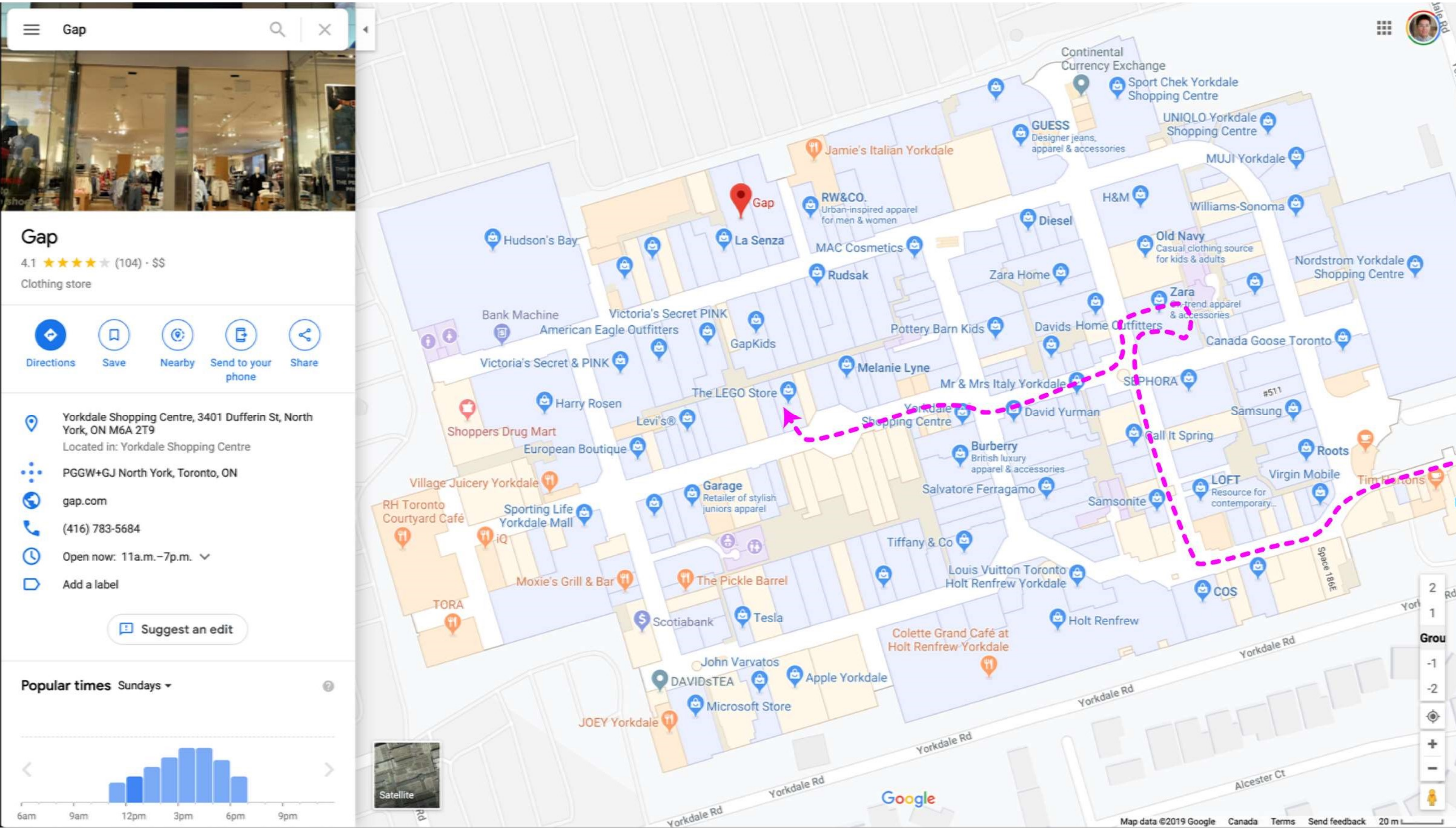
Future step

Anytime anywhere navigation

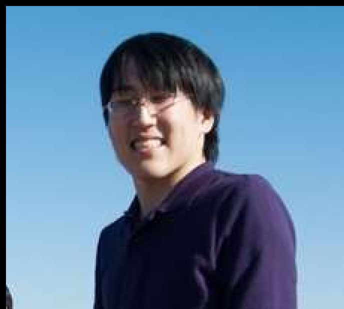


Anytime anywhere localization

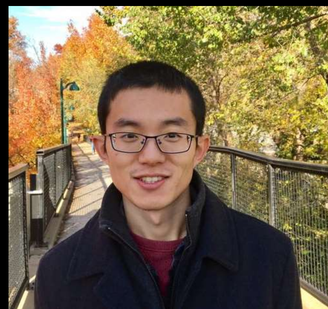



Gap
Gap
4.1 ★★★★★ (104) · $$
Clothing store
Directions
Save
Nearby
Send to your phone
Share
Yorkdale Shopping Centre, 3401 Dufferin St, North York, ON M6A 2T9
Located in: Yorkdale Shopping Centre
PGGW+GJ North York, Toronto, ON
gap.com
(416) 783-5684
Open now: 11a.m.–7p.m.
Add a label
Suggest an edit
Popular times
Sundays
6am
9am
12pm
3pm
6pm
9pm
Continental Currency Exchange
Sport Chek Yorkdale Shopping Centre
UNIQLO Yorkdale Shopping Centre
GUESS
Designer jeans, apparel & accessories
Jamie's Italian Yorkdale
MUJI Yorkdale
H&M
Williams-Sonoma
Gap
RW&CO.
Urban-inspired apparel for men & women
Diesel
Hudson's Bay
La Senza
MAC Cosmetics
Old Navy
Casual clothing source for kids & adults
Nordstrom Yorkdale Shopping Centre
Rudsak
Zara Home
Zara
Bank Machine
Victoria's Secret PINK
American Eagle Outfitters
GapKids
Pottery Barn Kids
Davids Home Outfitters
Canada Goose Toronto
Victoria's Secret & PINK
Melanie Lyne
Mr & Mrs Italy Yorkdale
SEPHORA
The LEGO Store
Harry Rosen
Yorkdale Shopping Centre
David Yurman
Samsung
Shoppers Drug Mart
Levi's®
Call It Spring
European Boutique
Burberry
British luxury apparel & accessories
Roots
Village Juicery Yorkdale
Garage
Retailer of stylish juniors apparel
Salvatore Ferragamo
LOFT
Resource for contemporary...
Virgin Mobile
Tim Hortons
RH Toronto Courtyard Café
Sporting Life Yorkdale Mall
Samsonite
iQ
Tiffany & Co
Moxie's Grill & Bar
The Pickle Barrel
Louis Vuitton Toronto
Holt Renfrew Yorkdale
COS
TORA
Scotiabank
Tesla
Holt Renfrew
Colette Grand Café at Holt Renfrew Yorkdale
John Varvatos
DAVIDsTEA
Apple Yorkdale
Microsoft Store
JOEY Yorkdale
Yorkdale Rd
Alcester Ct
Space 186E
Satellite
Google
Map data ©2019 Google
Canada
Terms
Send feedback
20 m


Wireless (RSSI, RTT, 5G)
Camera
Indoor map
Motion sensor (IMU)
[image from IEEE GlobalSpec]

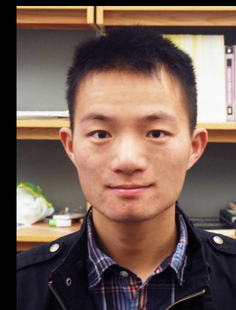


Satoshi Ikehata



Chen Liu

Huayi Zeng



Yiming Qian

Amin Shabani

Structured Geometry Modeling

Nelson Nauata

Fuyang Zhang

Mahsa Abyaneh

Sepid Hosseini

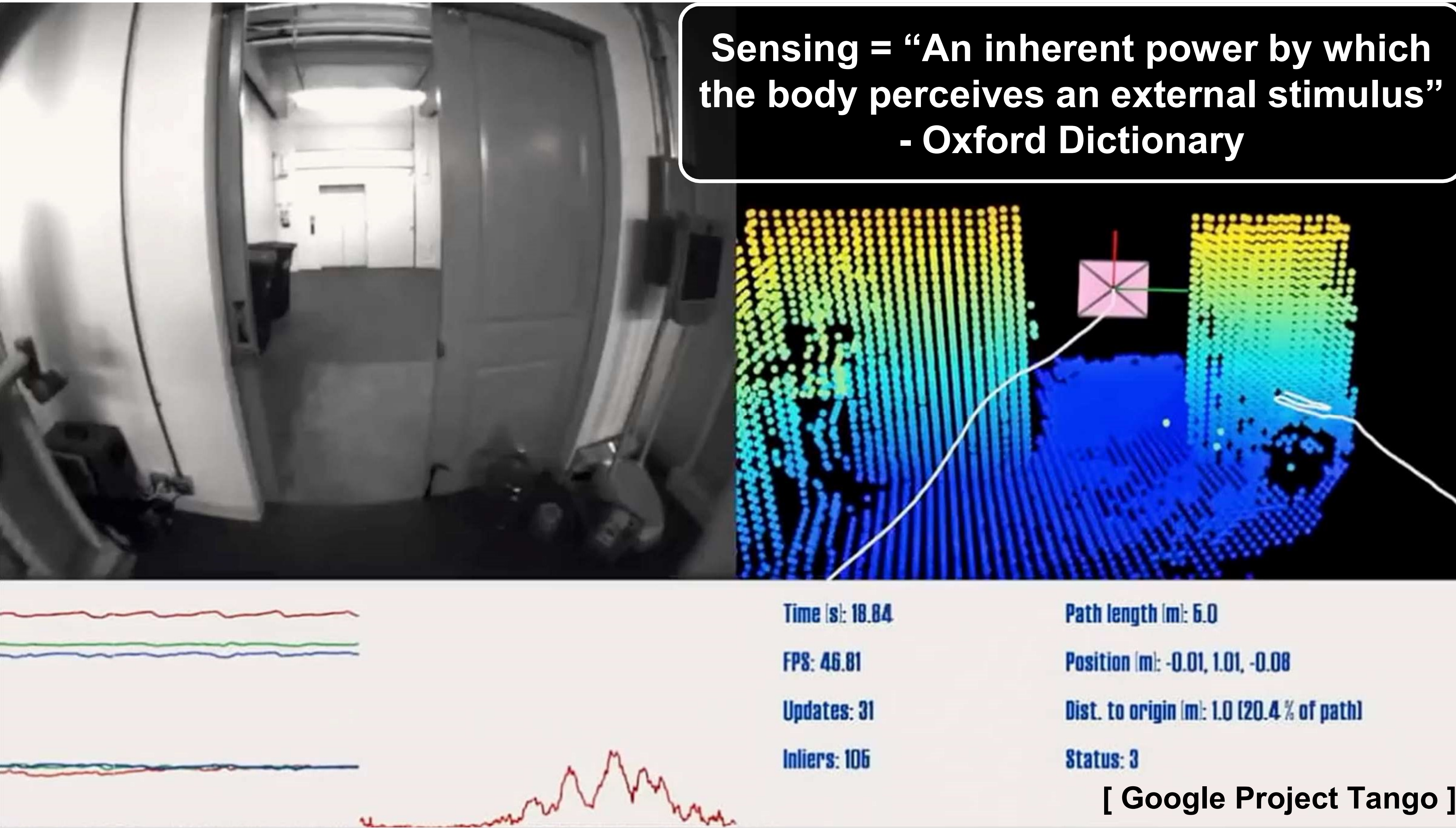
Weilian Song

Evolution of 3D Reconstruction Techniques

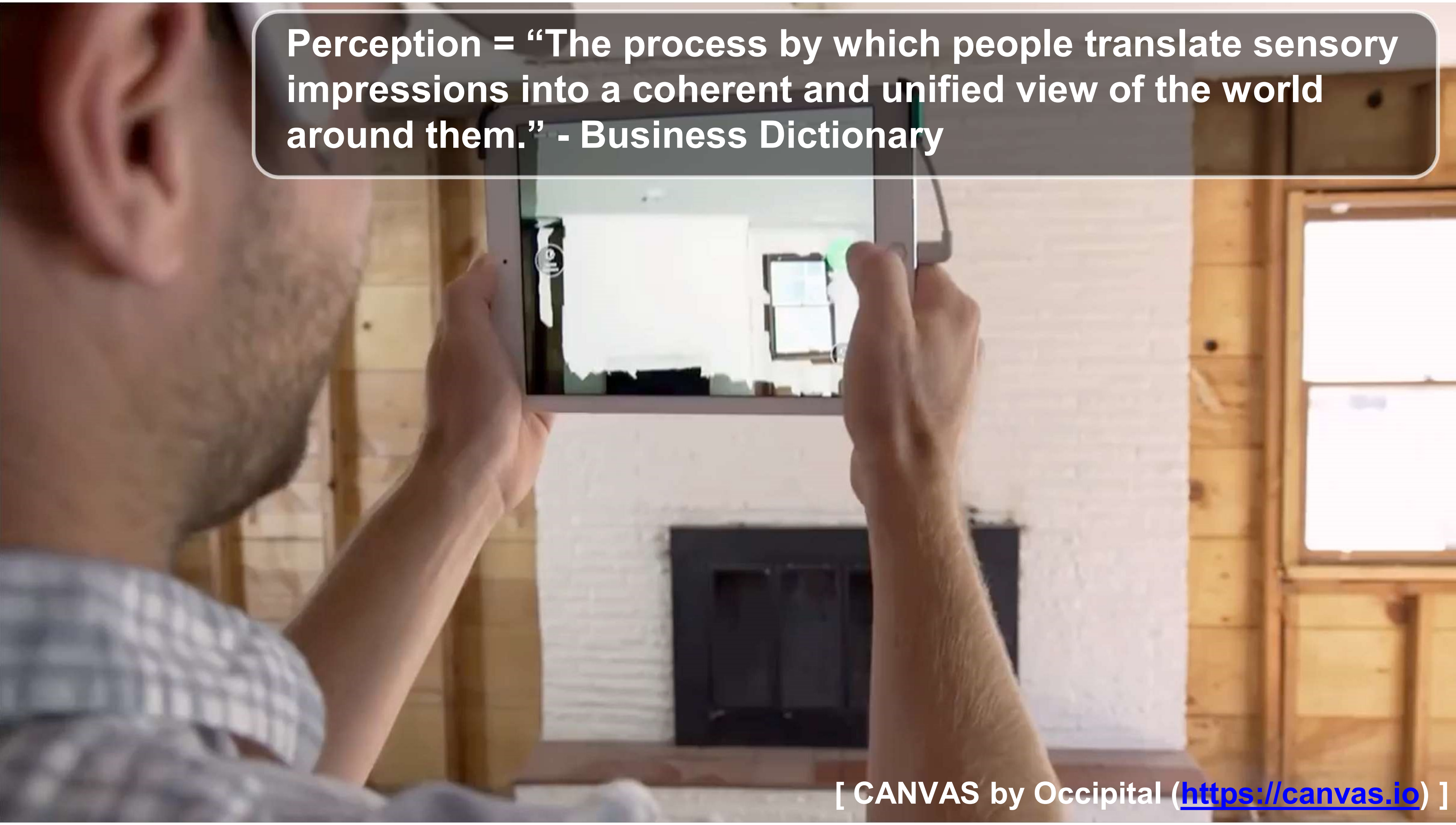
Sensing

Perception

Sensing = “An inherent power by which the body perceives an external stimulus”
- Oxford Dictionary



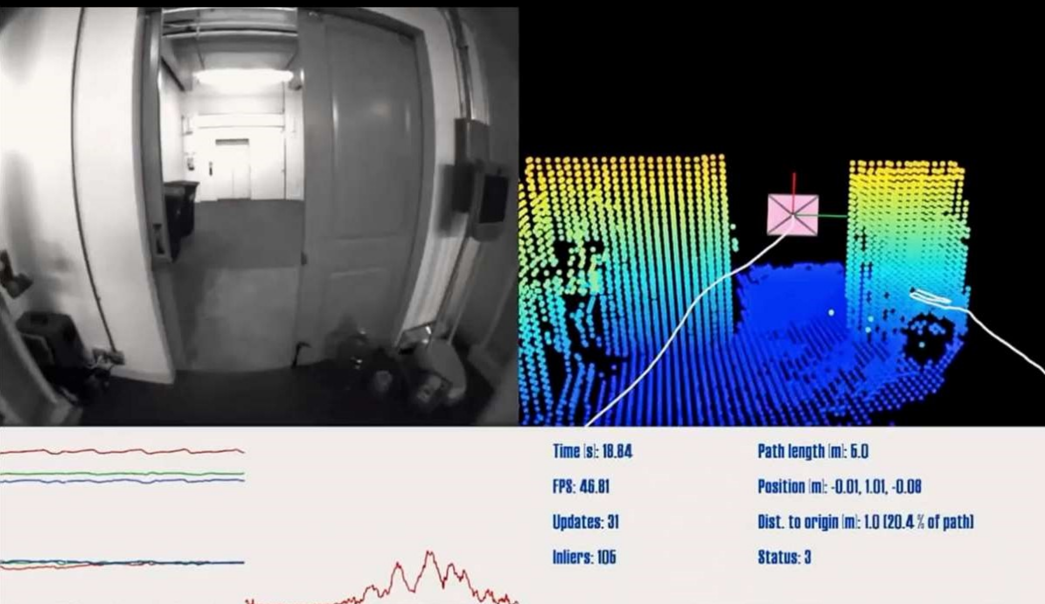
[Google Project Tango]



Perception = “The process by which people translate sensory impressions into a coherent and unified view of the world around them.” - Business Dictionary

[CANVAS by Occipital (https://canvas.io)]

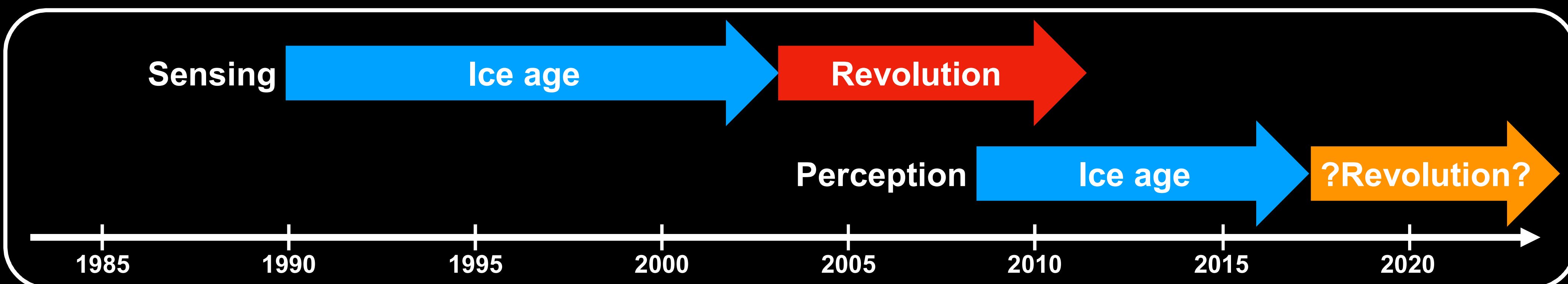
Sensing

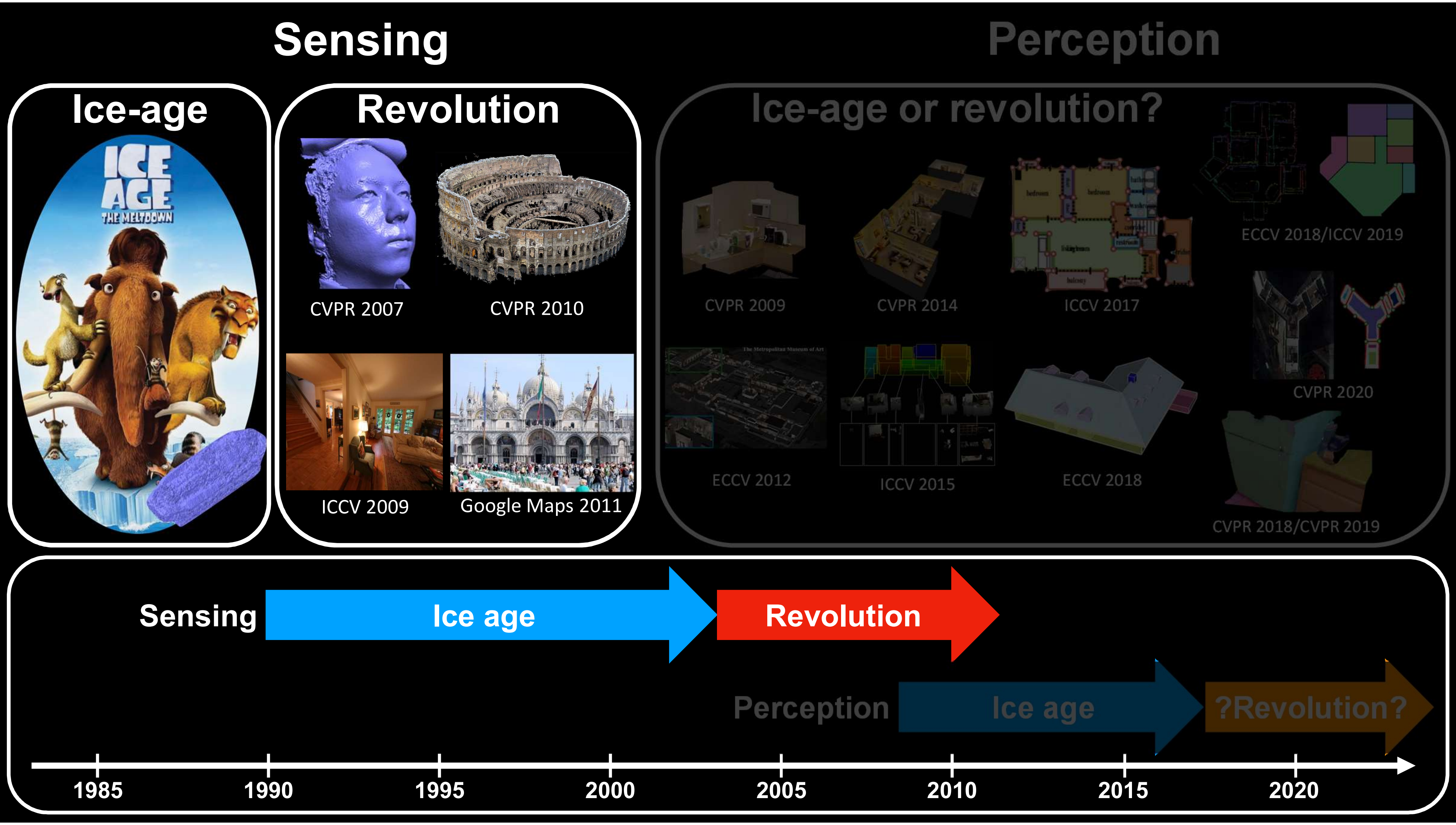


[Google Project Tango]

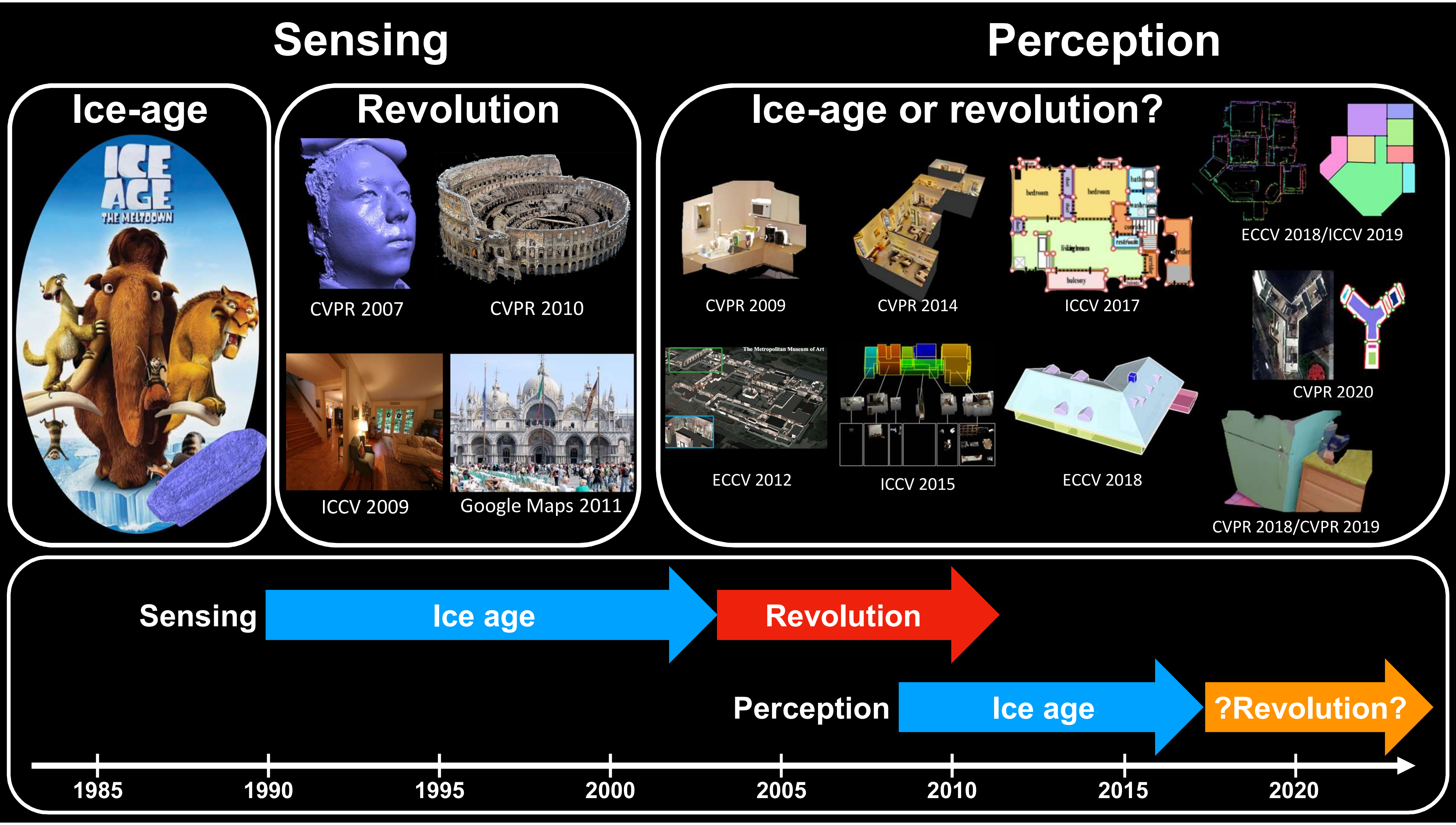
Perception

[CANVAS by Occipital (https://canvas.io)]





Sensing
Perception
Ice-age
Revolution
Ice-age or revolution?
ICE AGE THE MELTDOWN
CVPR 2007
CVPR 2010
ICCV 2009
Google Maps 2011
CVPR 2009
CVPR 2014
ICCV 2017
ECCV 2018/ICCV 2019
CVPR 2020
ECCV 2012
ICCV 2015
ECCV 2018
CVPR 2018/CVPR 2019
Sensing
Ice age
Revolution
Perception
Ice age
?Revolution?
1985
1990
1995
2000
2005
2010
2015
2020



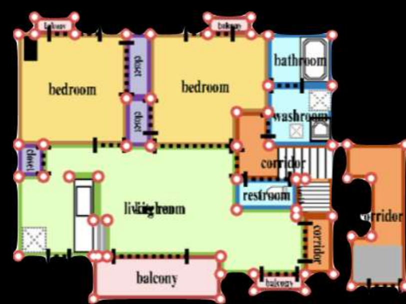
Sensing
Perception
Ice-age
ICE AGE
THE MELTDOWN
Revolution
CVPR 2007
CVPR 2010
ICCV 2009
Google Maps 2011
Ice-age or revolution?
CVPR 2009
CVPR 2014
ICCV 2017
ECCV 2018/ICCV 2019
ECCV 2012
ICCV 2015
ECCV 2018
CVPR 2020
CVPR 2018/CVPR 2019
Sensing
Ice age
Revolution
Perception
Ice age
?Revolution?
1985
1990
1995
2000
2005
2010
2015
2020

Perception

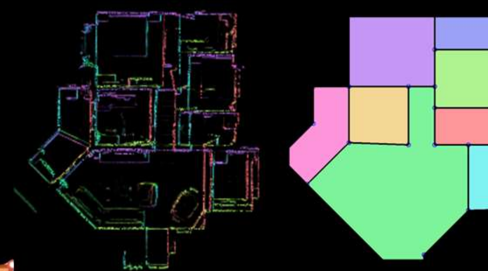
Ice-age → Revolution

CVPR 2009

CVPR 2014

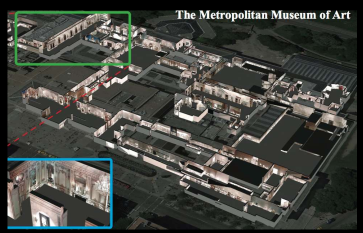


ICCV 2017

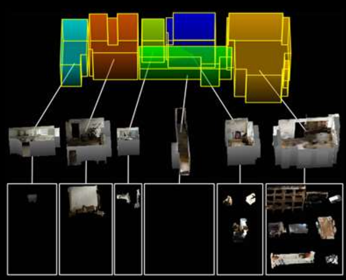


ECCV 2018/ICCV 2019

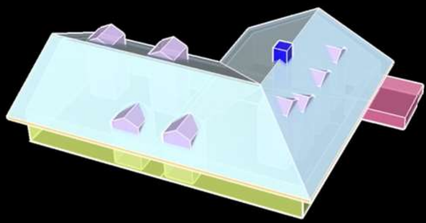
CVPR 2020



ECCV 2012



ICCV 2015



ECCV 2018

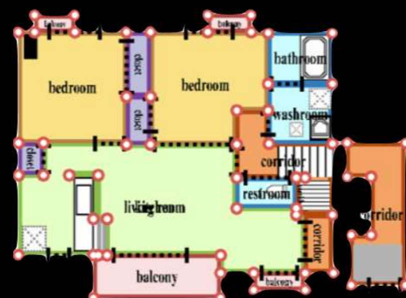
CVPR 2018/CVPR 2019

Perception

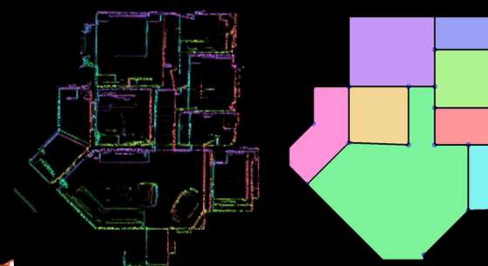
Ice-age **Revolution**

CVPR 2009

CVPR 2014

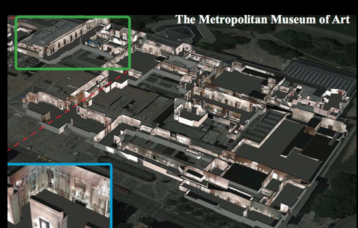


ICCV 2017

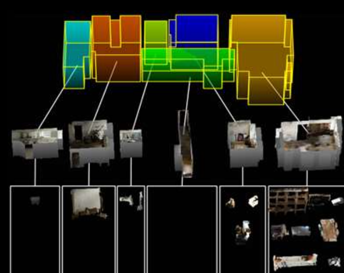


ECCV 2018/ICCV 2019

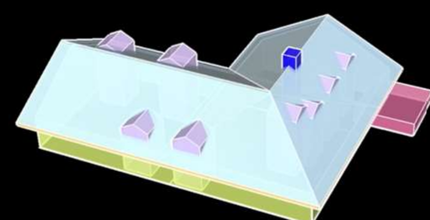
CVPR 2020



ECCV 2012

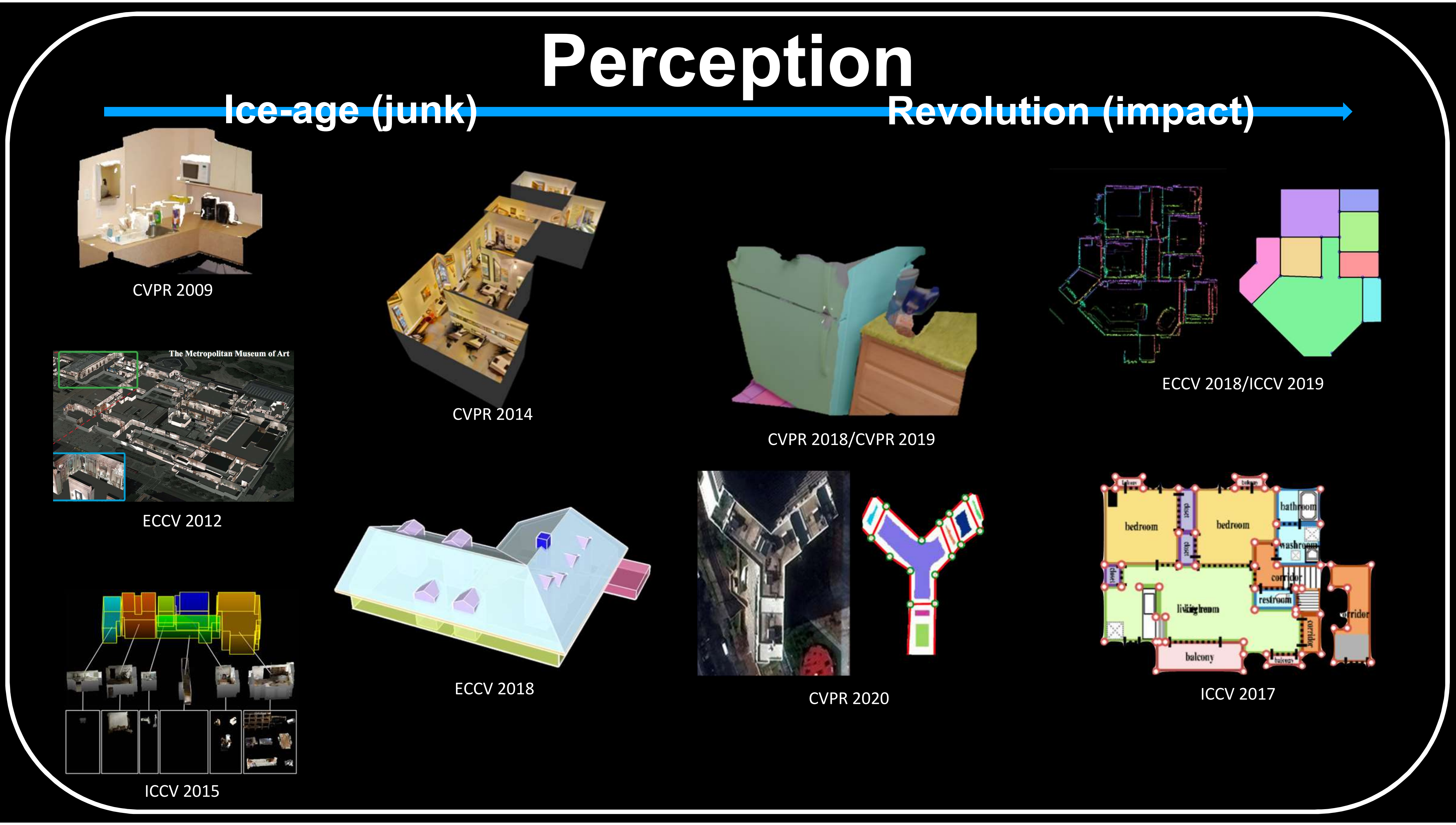


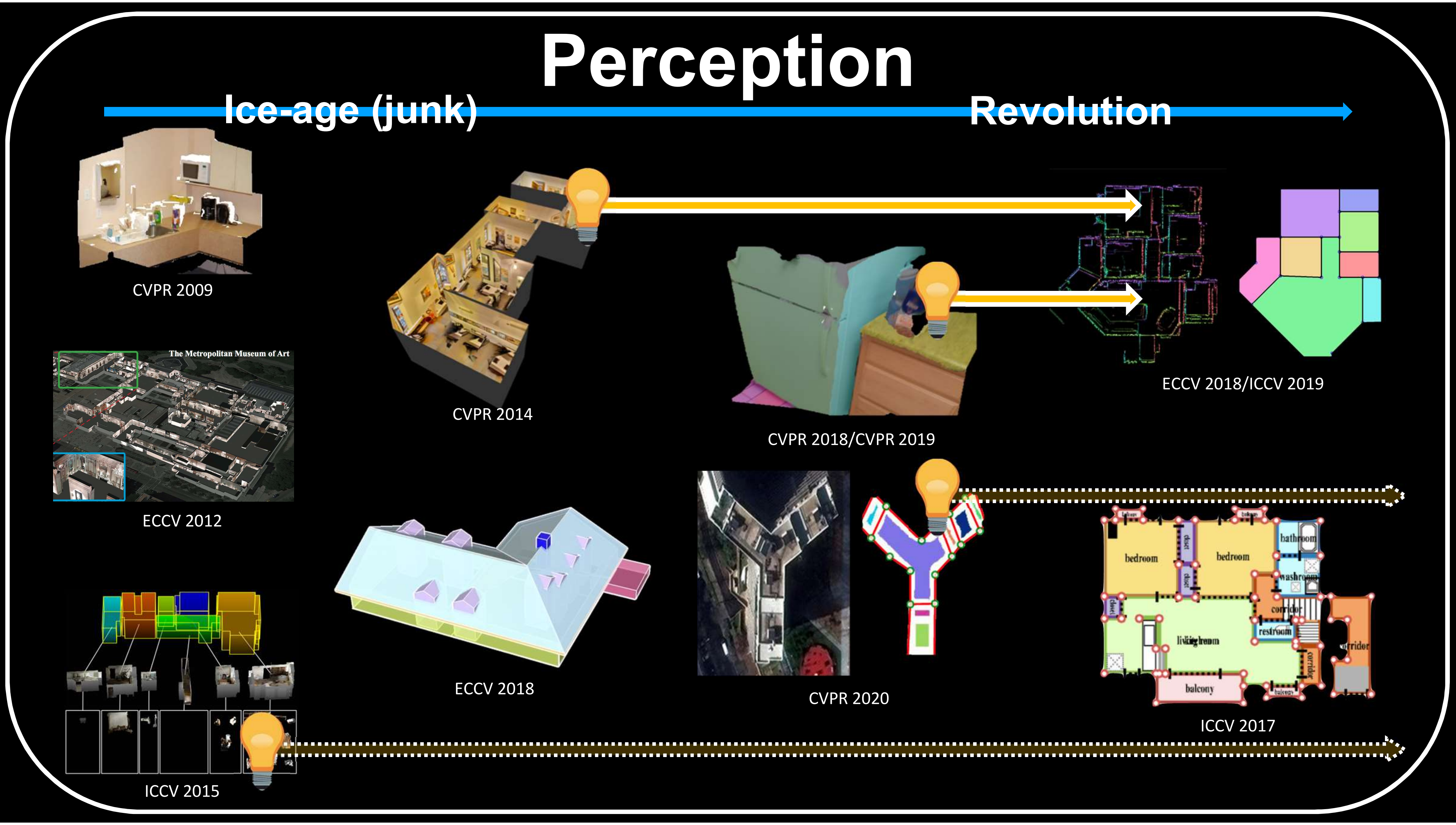
ICCV 2015

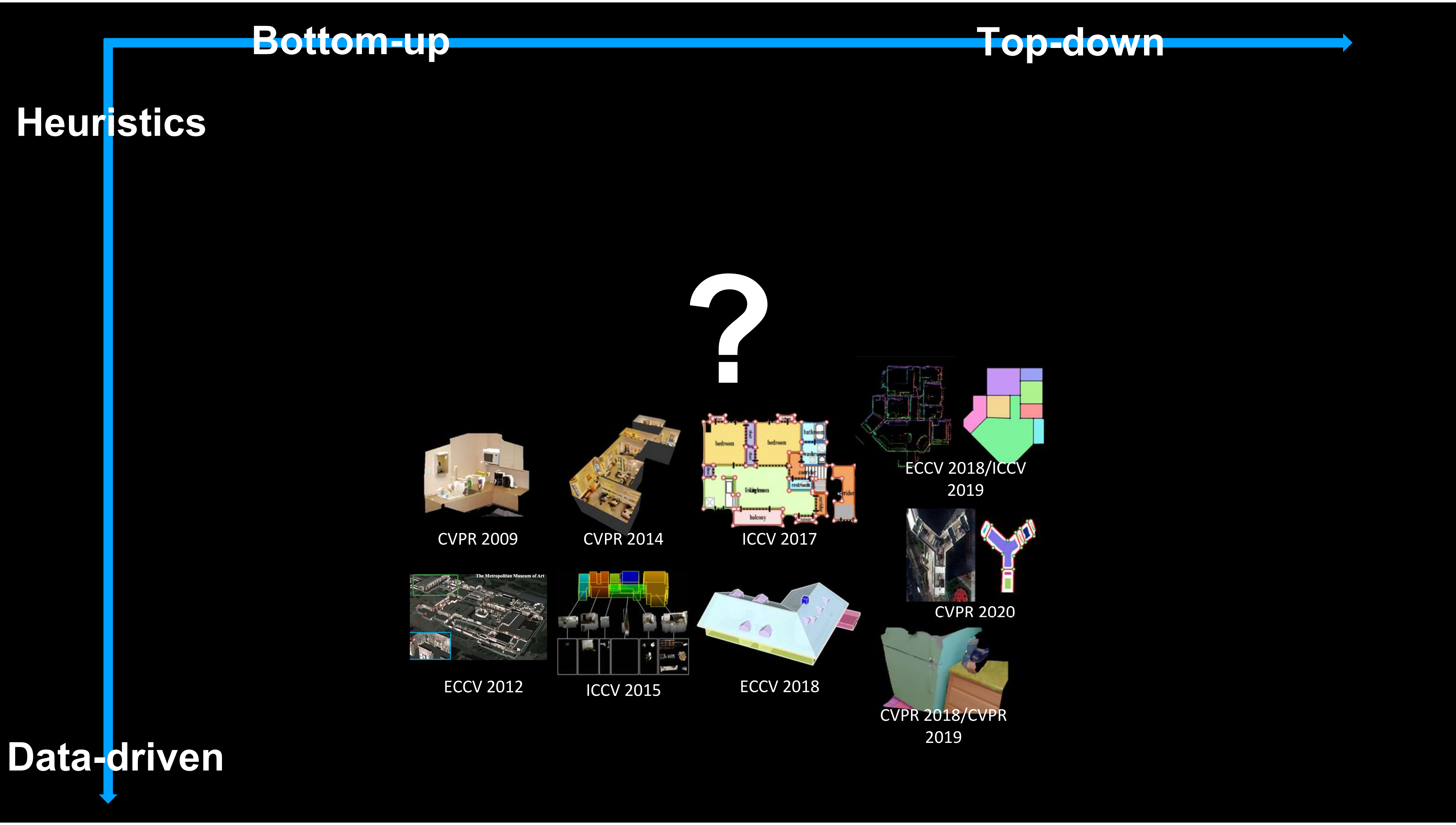


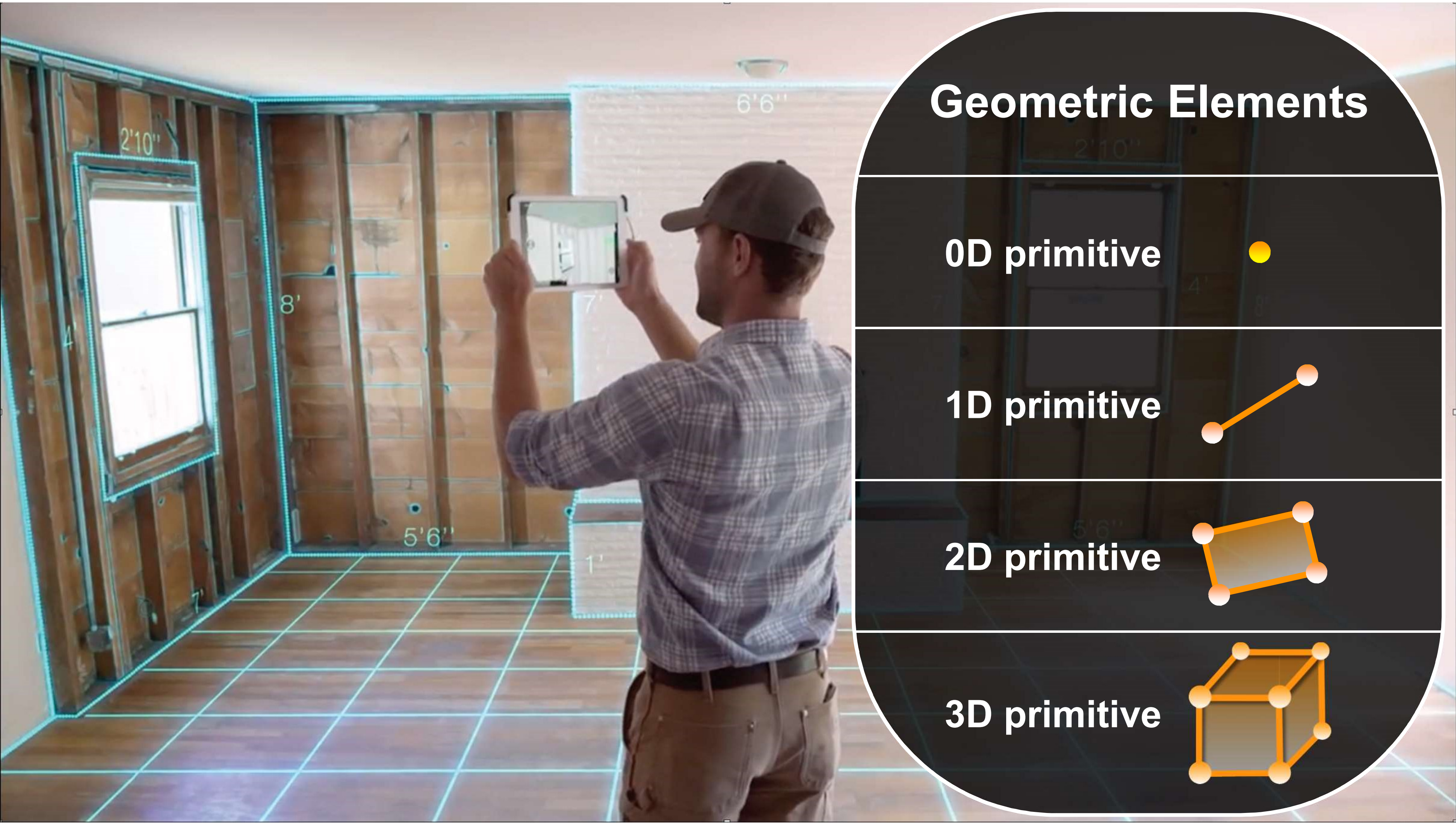
ECCV 2018

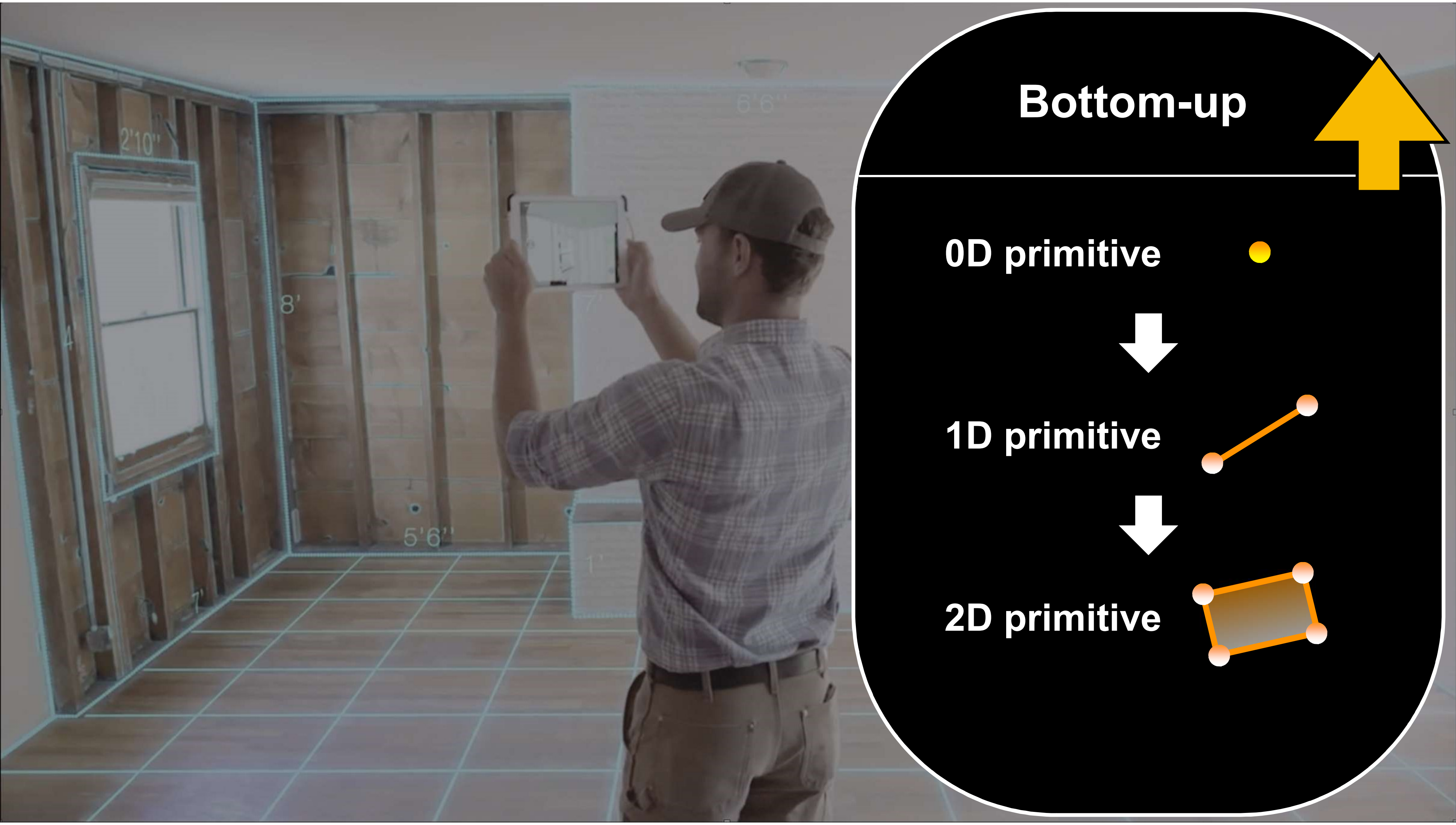
CVPR 2018/CVPR 2019

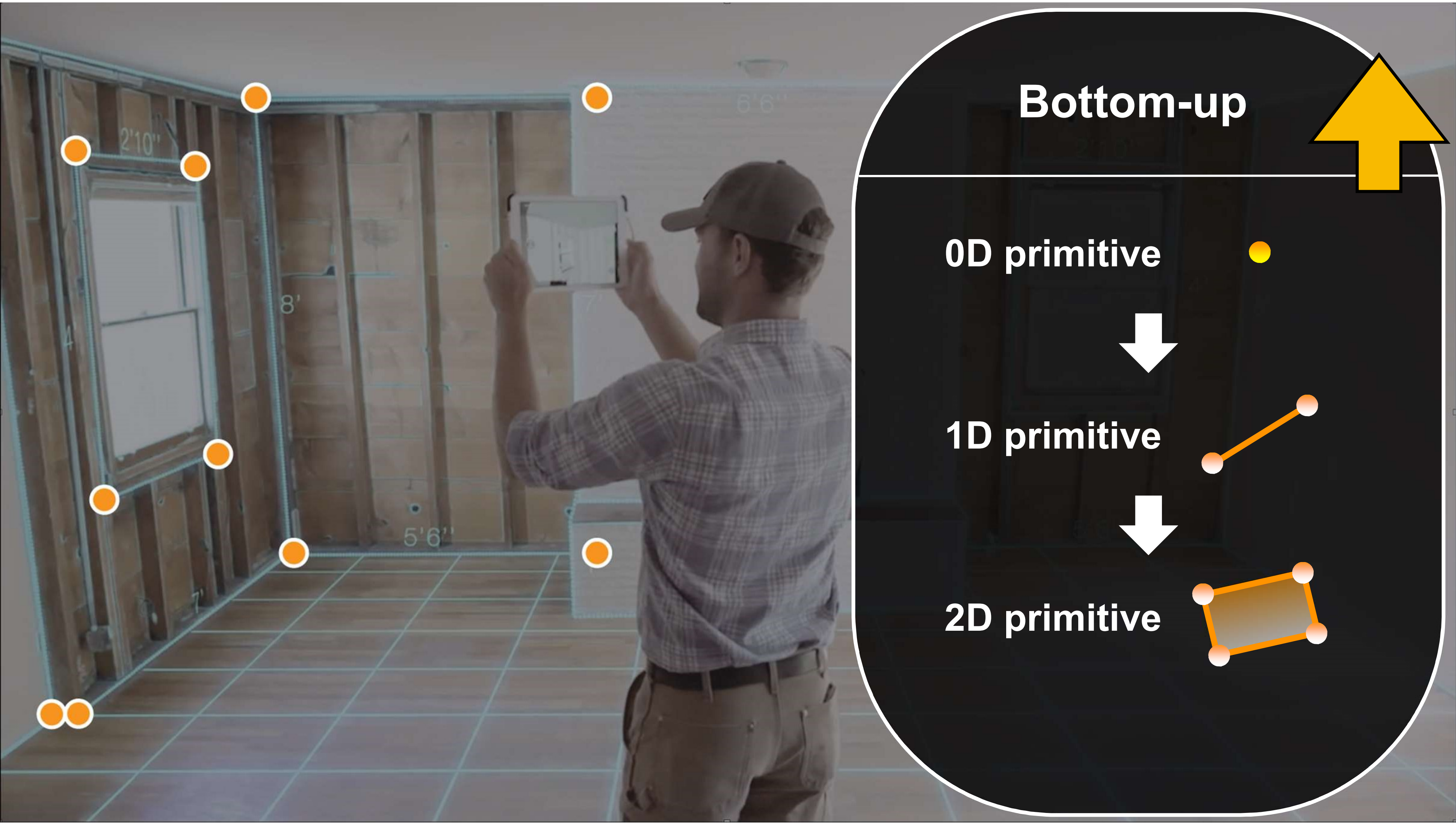

Perception
Ice-age (junk)
Revolution (impact)
CVPR 2009
The Metropolitan Museum of Art
ECCV 2012
ICCV 2015
CVPR 2014
ECCV 2018
CVPR 2018/CVPR 2019
CVPR 2020
ECCV 2018/ICCV 2019
bedroom
closet
bedroom
bathroom
washroom
corridor
restroom
living room
balcony
ICCV 2017

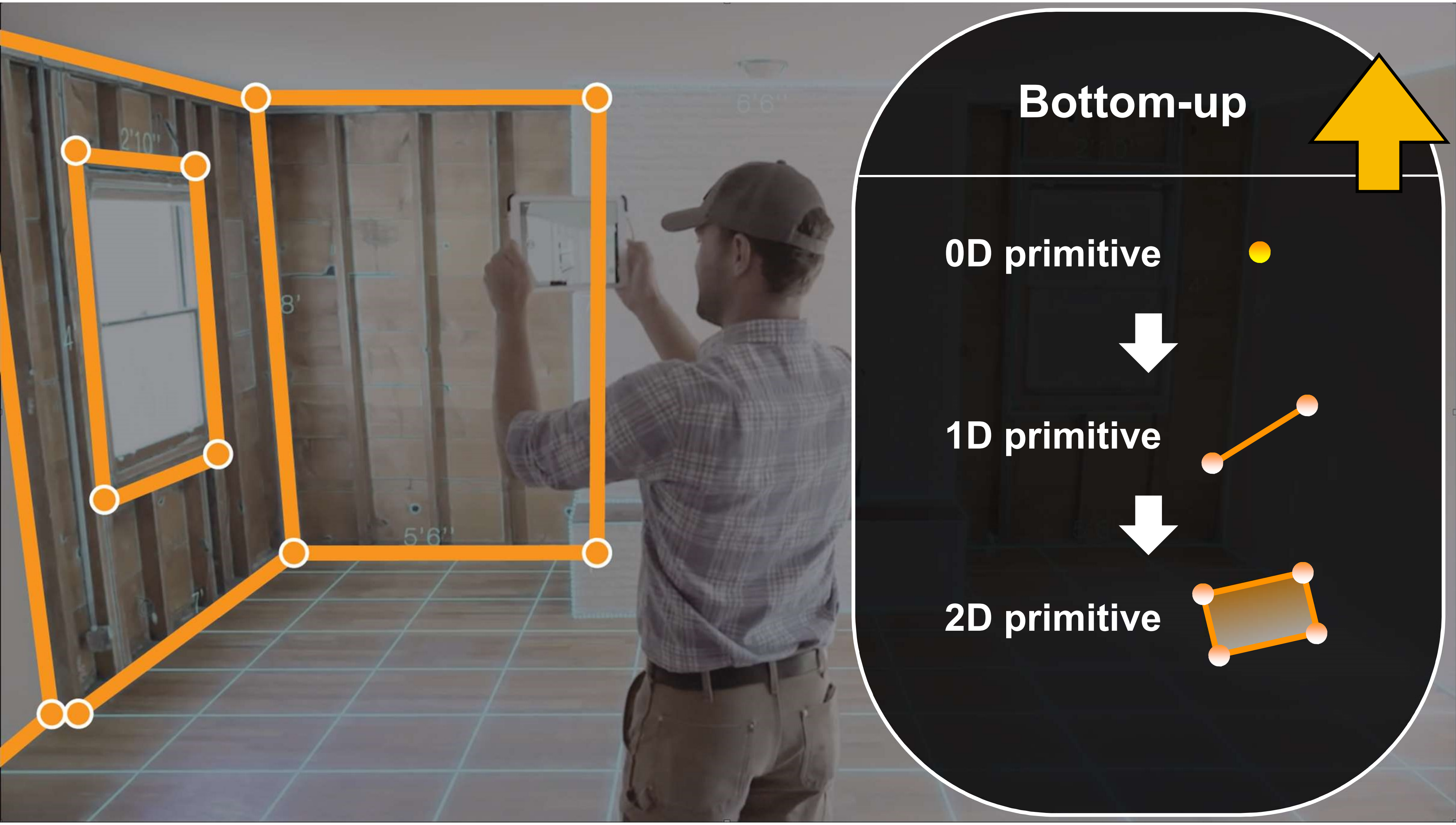

Perception
Ice-age (junk)
Revolution
CVPR 2009
CVPR 2014
CVPR 2018/CVPR 2019
ECCV 2018/ICCV 2019
The Metropolitan Museum of Art
ECCV 2012
ECCV 2018
CVPR 2020
bedroom
bedroom
bathroom
washroom
corridor
restroom
living room
balcony
ICCV 2017
ICCV 2015

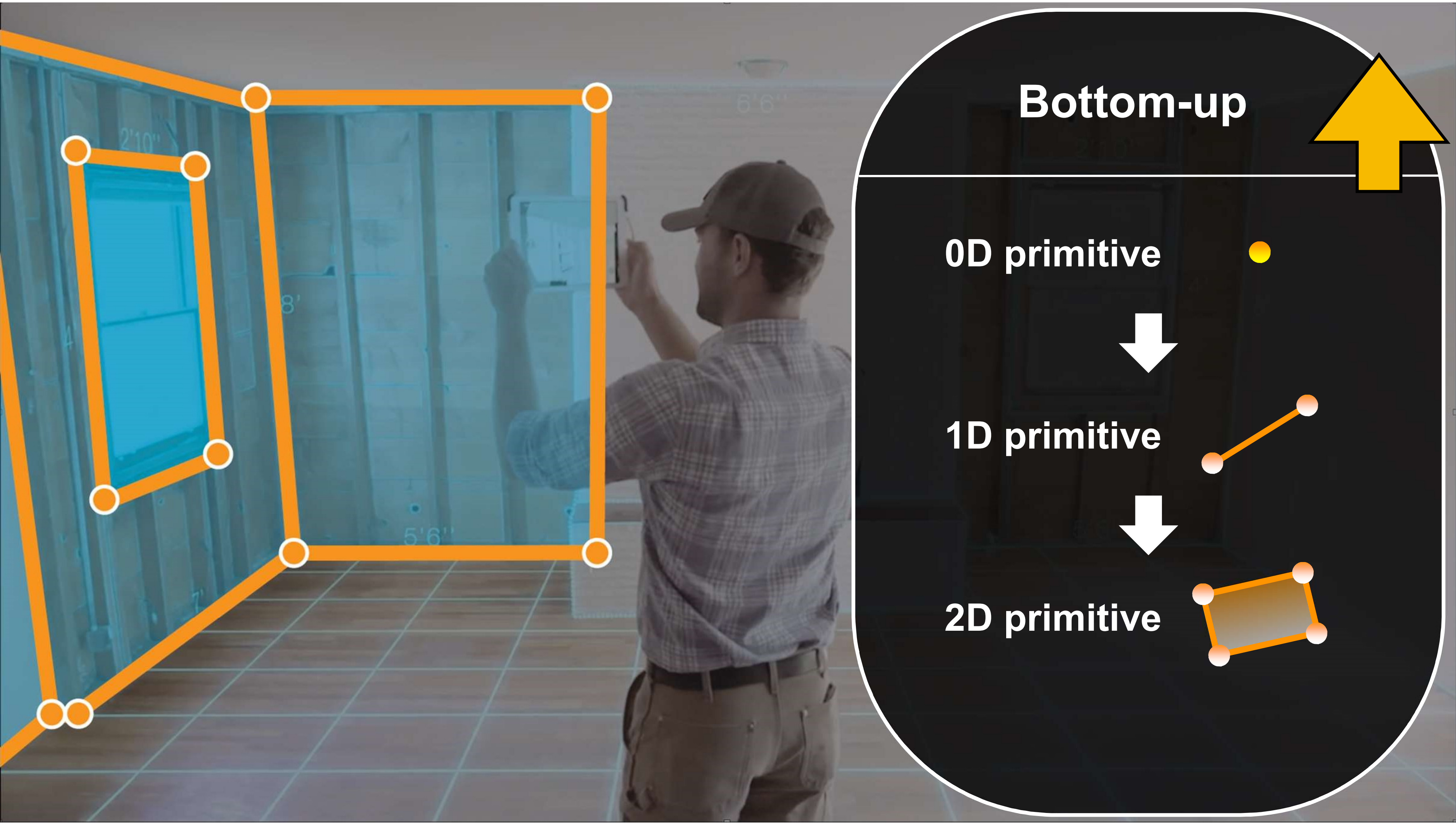

Bottom-up
Top-down
Heuristics
Data-driven
?
CVPR 2009
CVPR 2014
ICCV 2017
ECCV 2018/ICCV 2019
CVPR 2020
ECCV 2012
ICCV 2015
ECCV 2018
CVPR 2018/CVPR 2019


Geometric Elements
0D primitive
1D primitive
2D primitive
3D primitive
2'10"
8'
4'
5'6"
6'6"
7'
1'

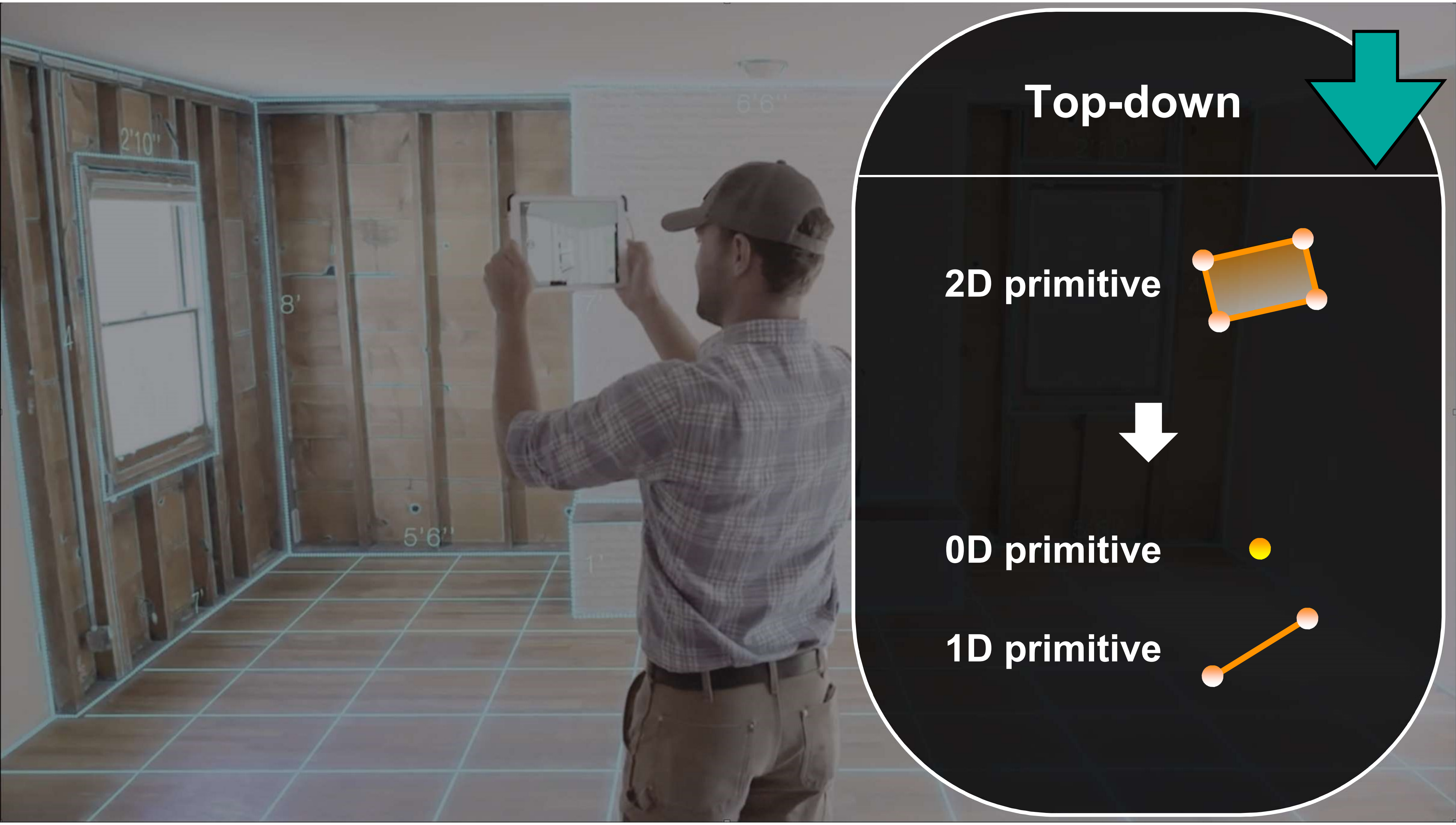

Bottom-up
0D primitive
1D primitive
2D primitive
2'10"
8'
5'6"

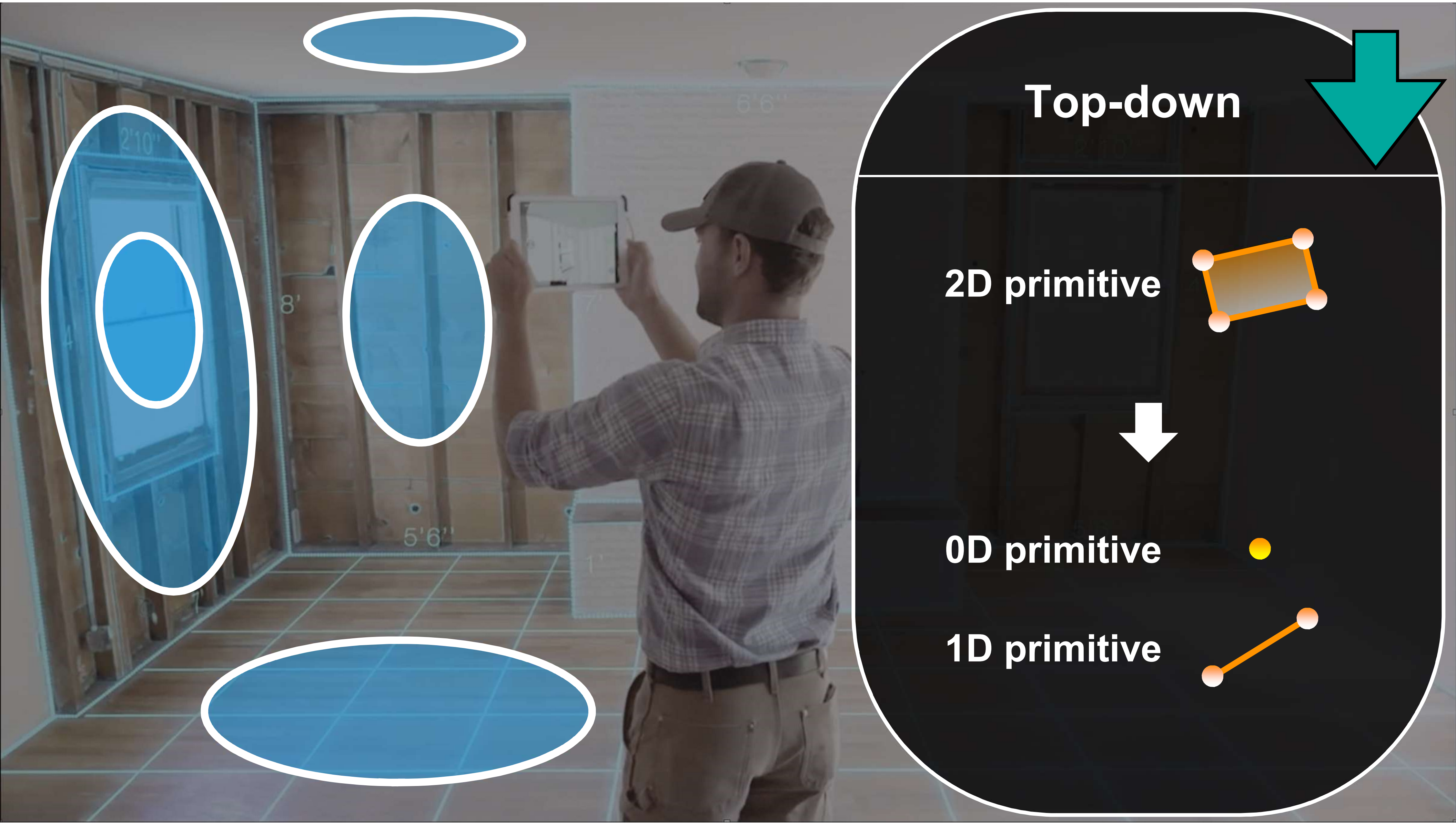

2'10"
8'
5'6"
6'6"
Bottom-up
0D primitive
1D primitive
2D primitive

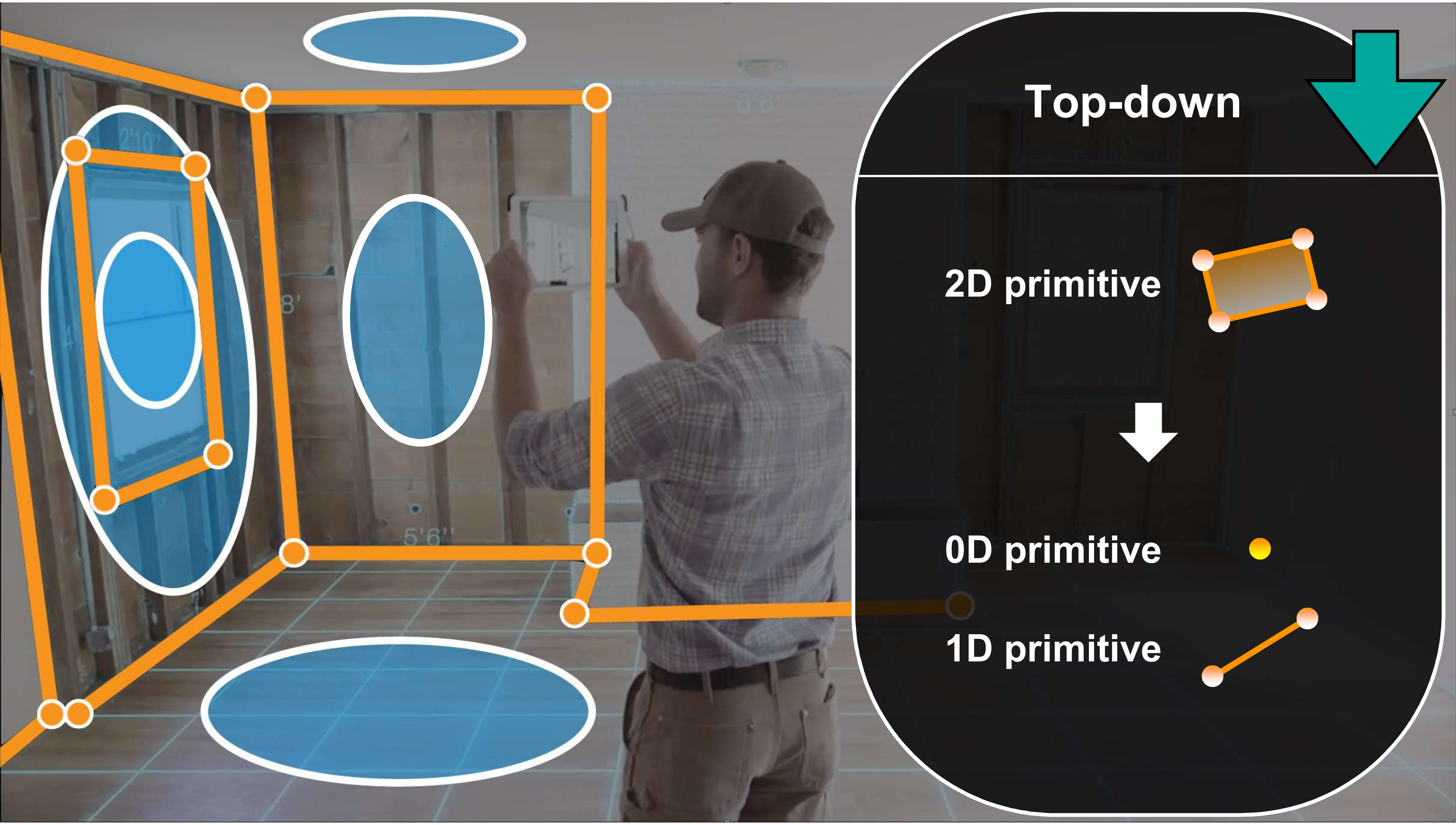

Bottom-up
0D primitive
1D primitive
2D primitive
2'10"
8'
5'6"
6'6"
7'



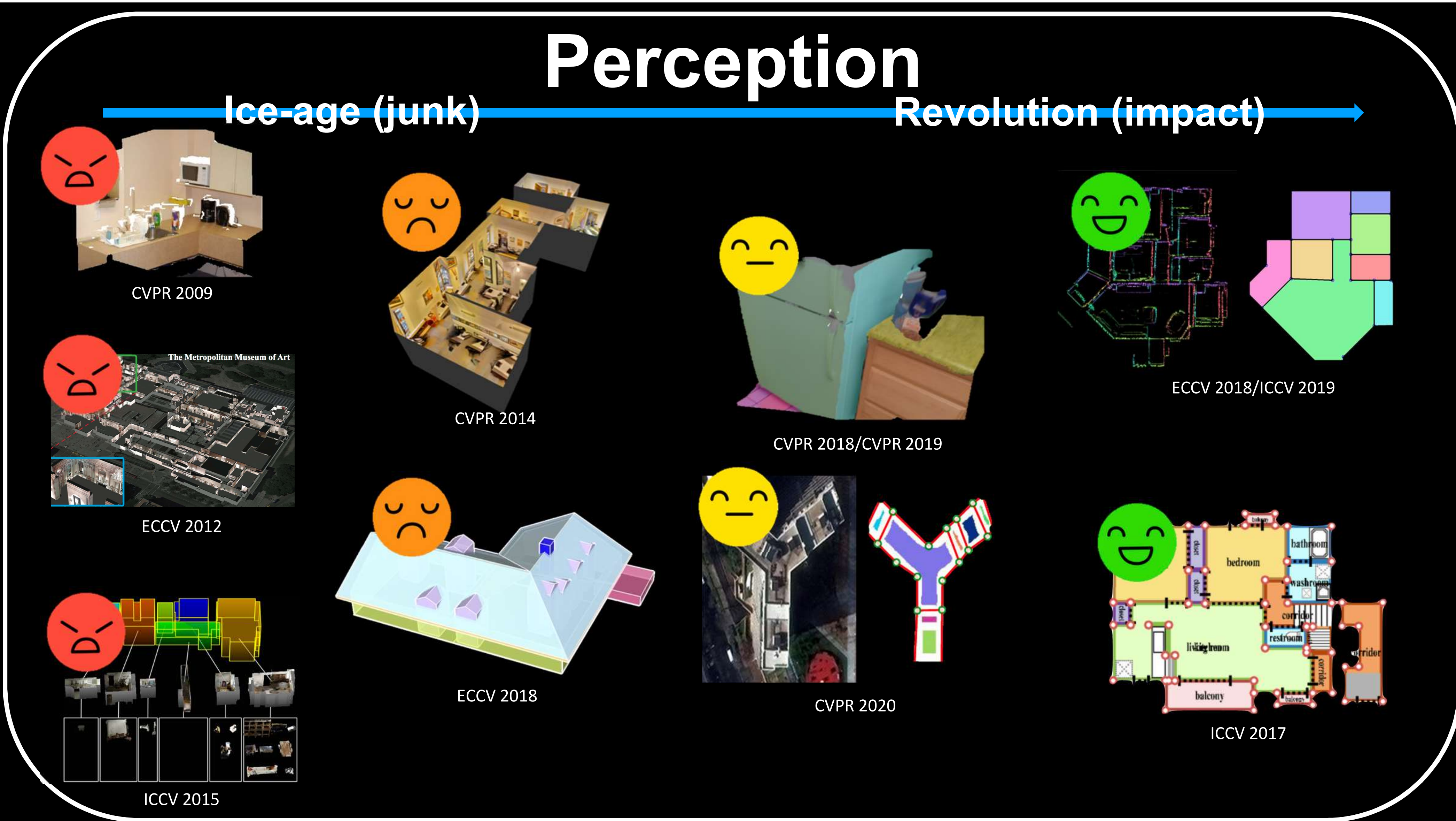
Bottom-up
0D primitive
1D primitive
2D primitive


Top-down
2D primitive
0D primitive
1D primitive
2'10"
8'
5'6"
6'6"
7'
1'

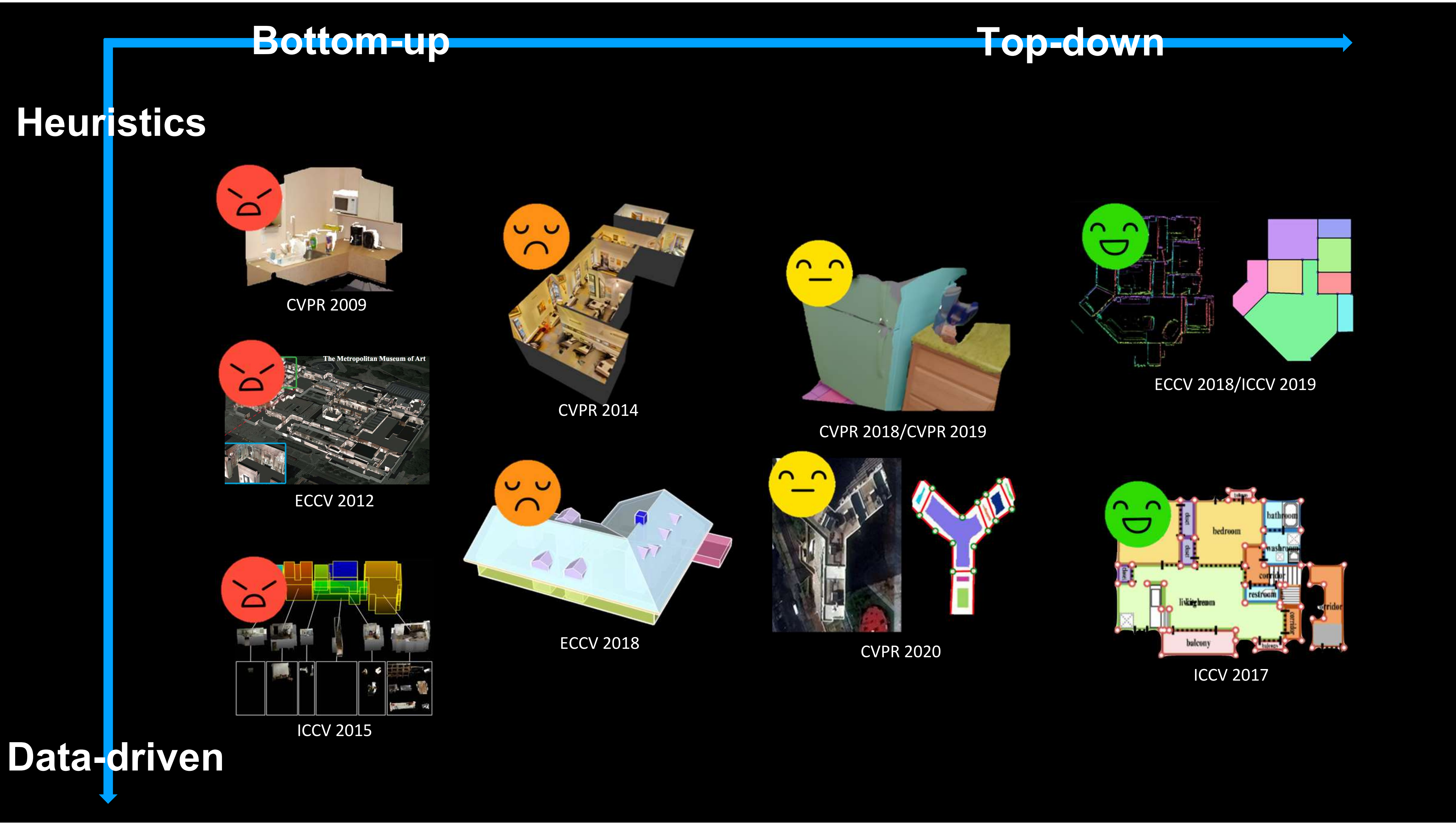

Top-down
2D primitive
0D primitive
1D primitive

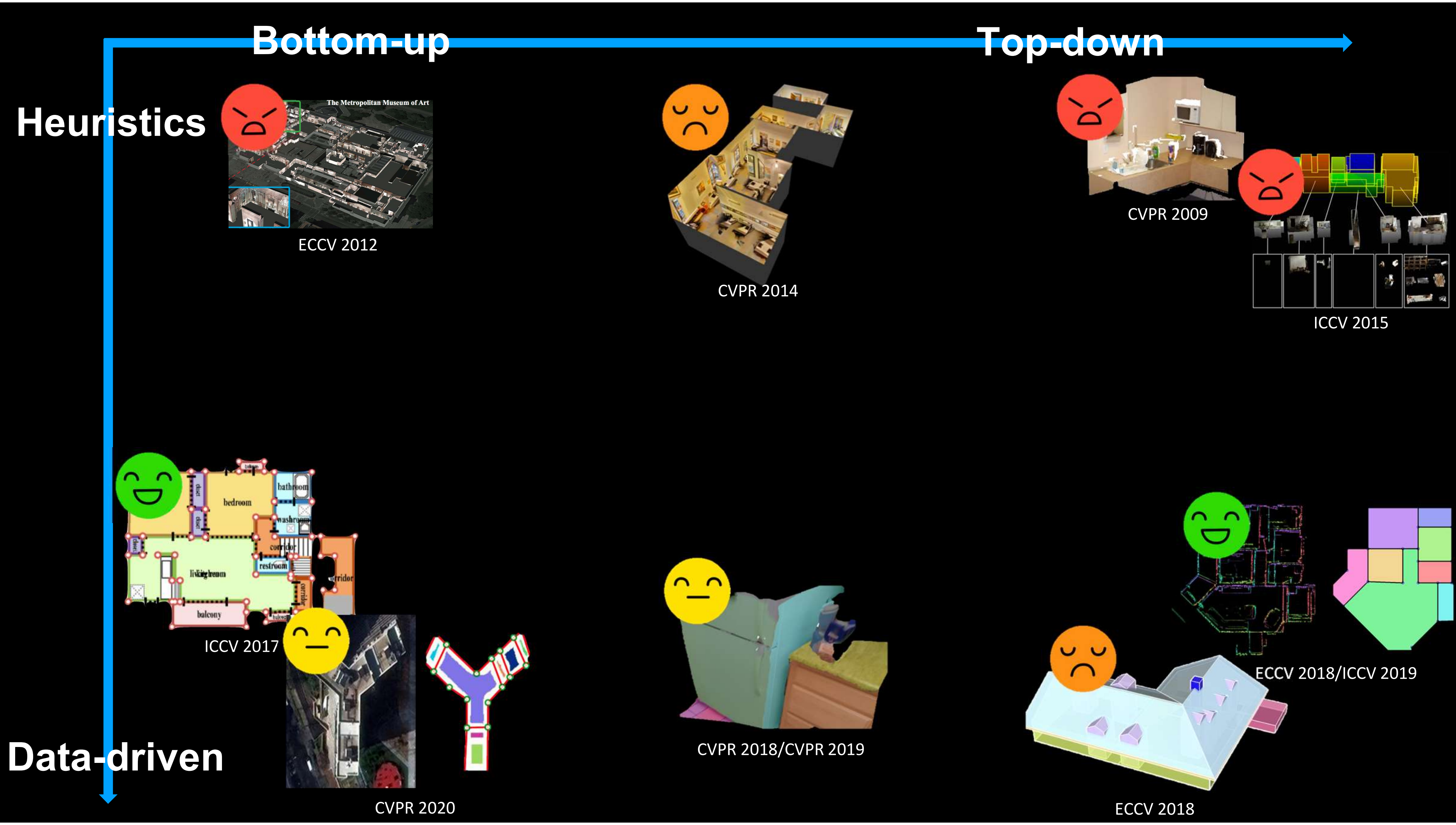


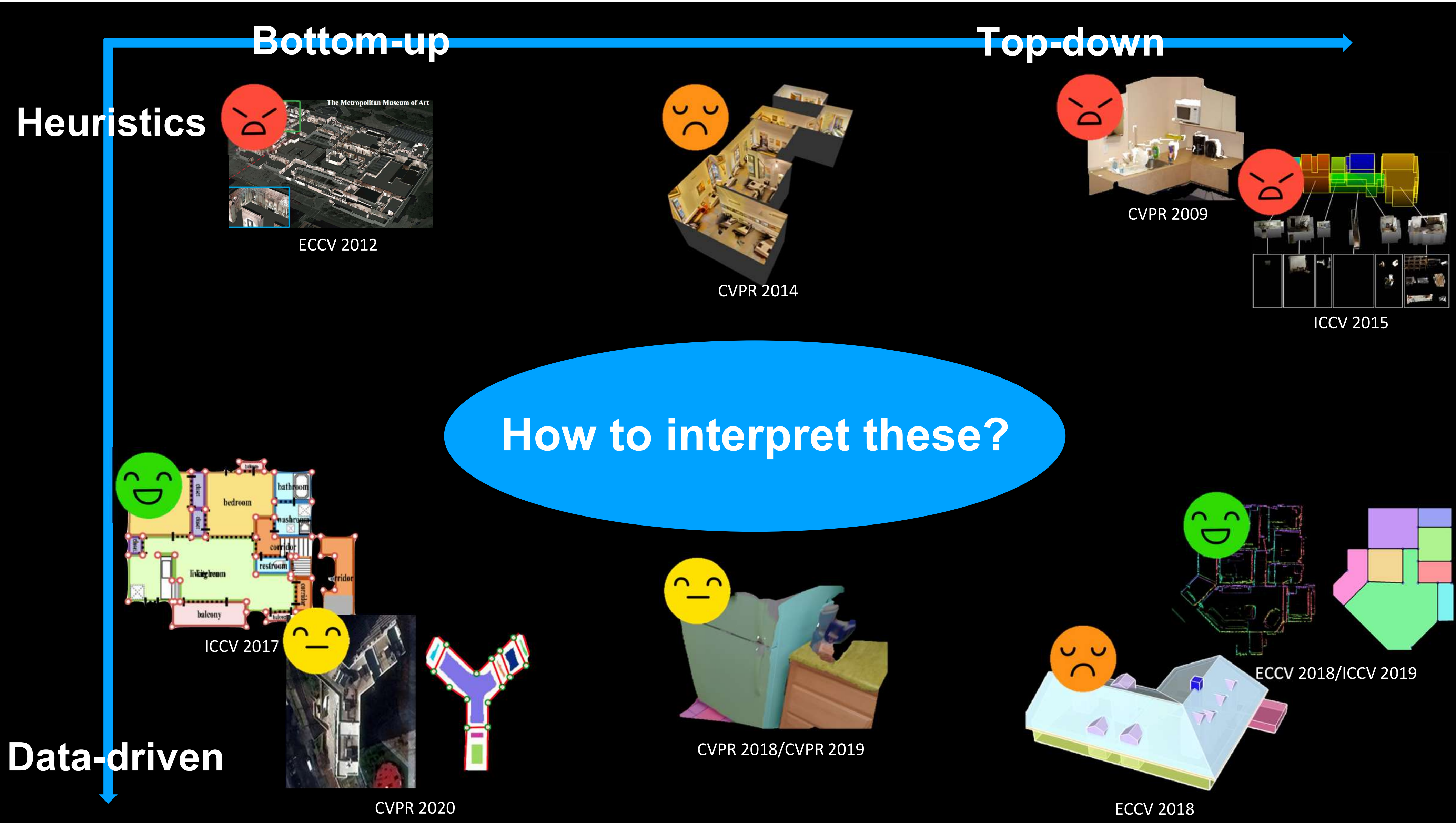
Top-down
2D primitive
0D primitive
1D primitive



Perception
Ice-age (junk)
Revolution (impact)
CVPR 2009
The Metropolitan Museum of Art
ECCV 2012
ICCV 2015
CVPR 2014
ECCV 2018
CVPR 2018/CVPR 2019
CVPR 2020
ECCV 2018/ICCV 2019
bedroom
bathroom
balcony
ICCV 2017


Bottom-up
Top-down
Heuristics
Data-driven
CVPR 2009
The Metropolitan Museum of Art
ECCV 2012
ICCV 2015
CVPR 2014
ECCV 2018
CVPR 2018/CVPR 2019
CVPR 2020
ECCV 2018/ICCV 2019
bedroom
bathroom
balcony
ICCV 2017

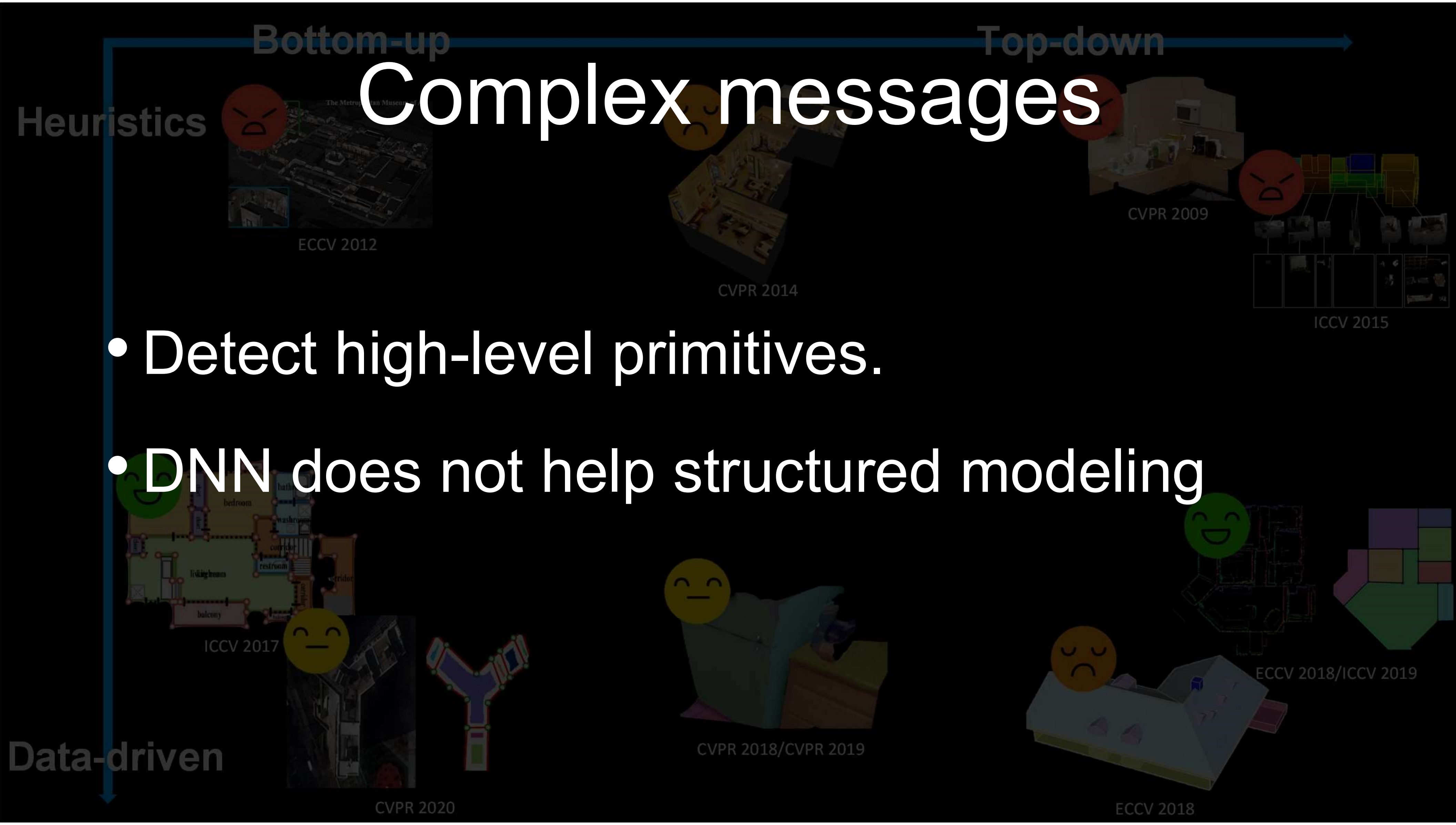

Bottom-up
Top-down
Heuristics
Data-driven
The Metropolitan Museum of Art
ECCV 2012
CVPR 2014
CVPR 2009
ICCV 2015
bedroom
bathroom
washroom
corridor
restroom
living room
balcony
ICCV 2017
CVPR 2020
CVPR 2018/CVPR 2019
ECCV 2018/ICCV 2019
ECCV 2018

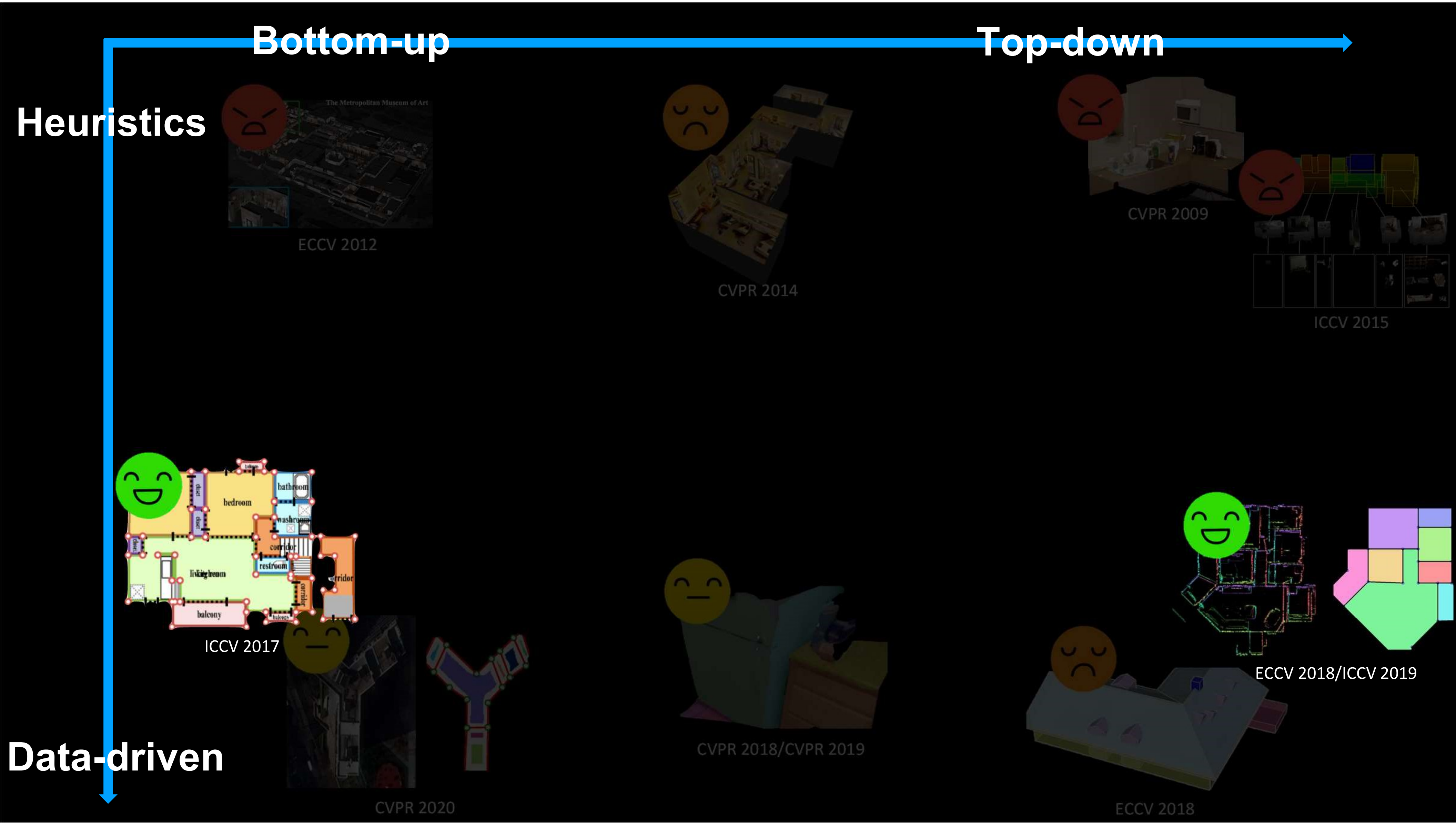


Bottom-up
Top-down
Heuristics
Data-driven
ECCV 2012
CVPR 2014
CVPR 2009
ICCV 2015
How to interpret these?
ICCV 2017
CVPR 2020
CVPR 2018/CVPR 2019
ECCV 2018/ICCV 2019
ECCV 2018

Complex messages

- Detect high-level primitives.
- DNN does not help structured modeling



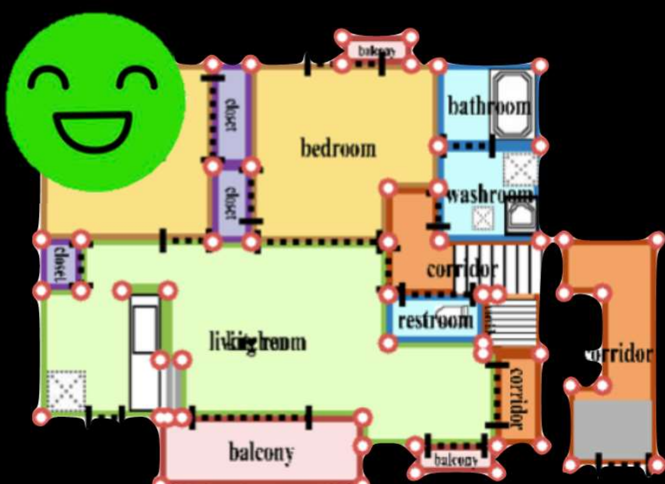


Bottom-up
Top-down
Heuristics
Data-driven
ECCV 2012
CVPR 2014
CVPR 2009
ICCV 2015
ICCV 2017
CVPR 2020
CVPR 2018/CVPR 2019
ECCV 2018/ICCV 2019
ECCV 2018
bedroom
bathroom
washroom
corridor
restroom
living room
balcony
corridor

Floorplan vectorization from scan

Bottom-up

1. Corners by DNN
2. Edges/regions by optimization

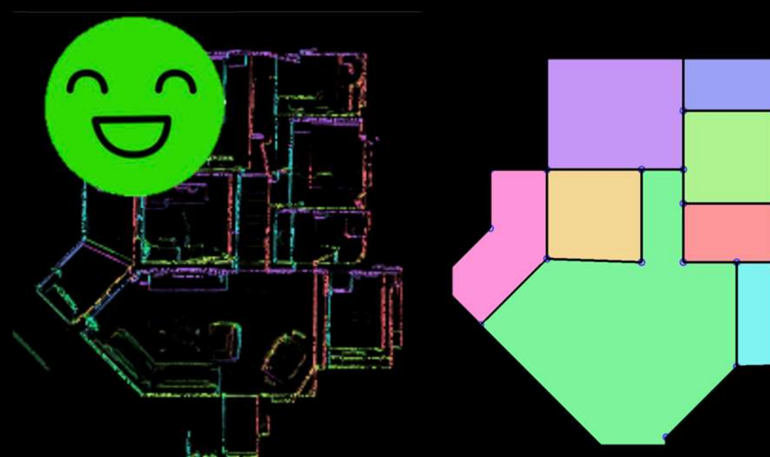


ICCV 2017

Floorplan reconstruction from 3D points

Top-down

1. Regions by DNN
2. Edges/corners by optimization

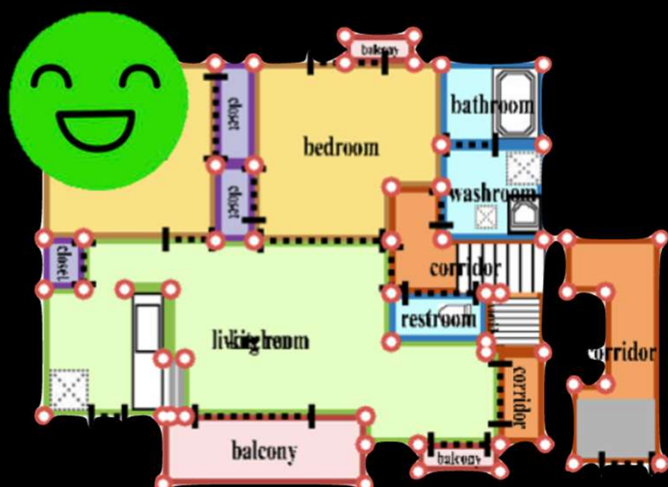


ECCV 2018/ICCV 2019

Floorplan vectorization from scan

Bottom-up

1. Corners by DNN
2. Edges/regions by optimization

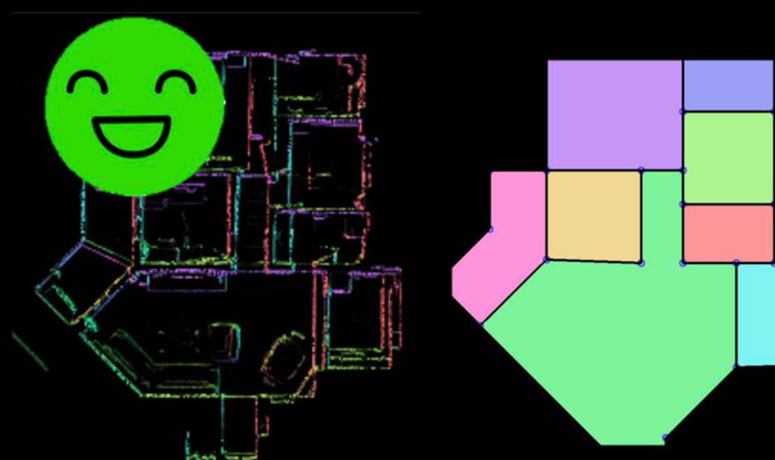


ICCV 2017

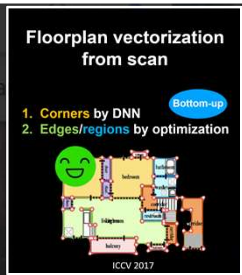
Floorplan reconstruction from 3D points

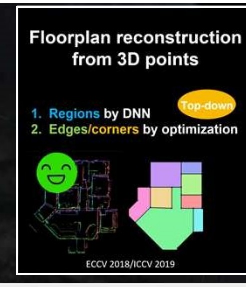
Top-down

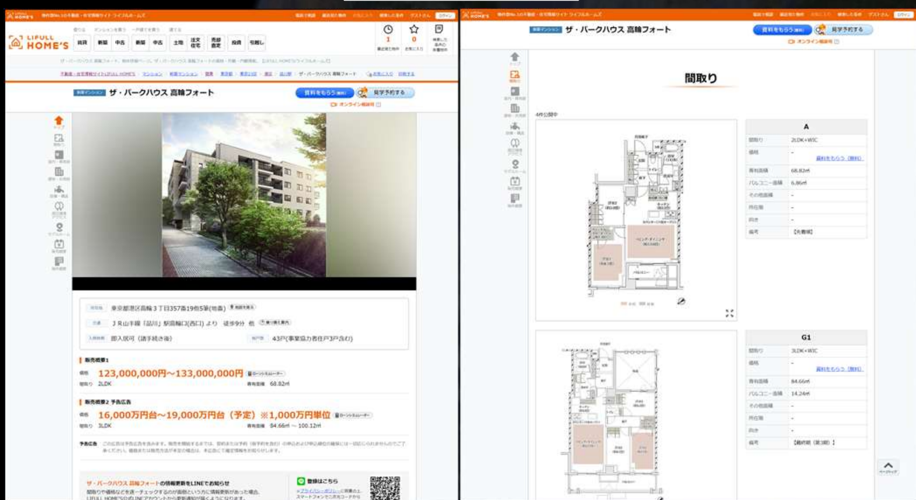
1. Regions by DNN
2. Edges/corners by optimization

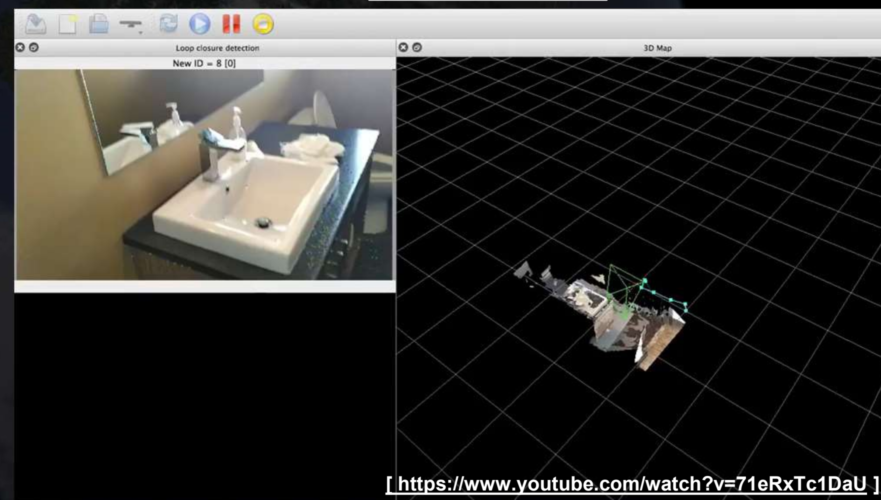


ECCV 2018/ICCV 2019









vectorize

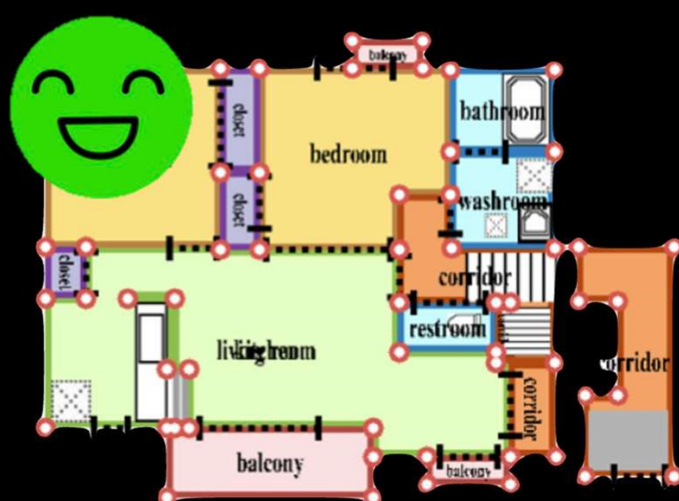
reconstruct

1. House information extraction
2. House price prediction
3. Remodeling
4. …

Floorplan vectorization from scan

Bottom-up

1. Corners by DNN
2. Edges/regions by optimization



ICCV 2017


English

大学共同利用機関法人 情報・システム研究機構 国立情報学研究所 National Institute of Informatics

IDR 情報学研究データリポジトリ

HOME | データ一覧 | 研究成果一覧 | ユーザフォーラム | 組織 | 関連リンク | 問い合わせ

> HOME > データ一覧 > LIFULL HOME'Sデータセット

- 民間企業提供データ
  - Yahoo!データセット
  - 楽天データセット
  - ニコニコデータセット
  - リクルートデータセット
  - クックパッドデータセット
  - LIFULL HOME'Sデータセット
  - 不満調査データセット
  - Sansanデータセット
  - インテージデータセット
  - オリコンデータセット
  - ダイエット口コミデータセット
- NTCIRテストコレクション
- 音声コーパス
- 研究者提供データ
  - グループコミュニケーションコーパス（TDU-NEDO）

LIFULL HOME'Sデータセット（旧名称: HOME'Sデータセット）

国立情報学研究所が株式会社LIFULL（旧社名 株式会社ネクスト）から提供を受けて研究者に提供しているデータセットです。

2019/09/12 更新

データ概要

不動産・住宅情報サイトLIFULL HOME'Sに掲載されたデータです。

- **賃貸物件スナップショットデータ**（2015年9月時点，賃貸物件データ＋画像データ）
  全国約533万件についての賃料，面積，立地（市区町村，郵便番号，最寄り駅，徒歩分），築年数，間取り，建物構造，諸設備などのデータと，各物件に対する間取り図や室内写真など約8,300万枚の画像データです。IDはユニーク番号に変換済みで，特定の物件に紐付く属性は含んでおりません。賃貸物件データはTSV形式のファイルで約1.6GBです。画像データは最大横120ピクセル×縦120ピクセルのJPEG形式で，圧縮ファイルで約210GBとなります。画像のメタデータには「玄関」「キッチン」といった画像の種別や，一部にはフリーテキストによる説明が付与されています。
- **高精細度間取り図画像データ**（賃貸物件スナップショットデータに対応）
  賃貸物件スナップショットの画像データのうち，間取り図に関しての高精細度版の画像データ約515万枚です。JPEG形式で，圧縮ファイルで約140GBとなります。本データに関しては別途お申し込みが必要です（詳細は下記**「お申し込み」**欄をご覧ください）。
- **賃貸・売買物件月次データ**（2015年7月～2017年6月，24ヶ月） 2018-12-05 新規
  賃料もしくは価格，面積，立地（市区町村，郵便番号，最寄り駅，徒歩分，緯度・経度），築年数，間取り，建物構造，諸設備などのデータです。24ヶ月の各々の期間（1日～末日）に掲載されていた物件情報を抽出したものです。物件IDは賃貸物件スナップショットデータおよび高精細度画像データとは対応していません。また，同一物件については機械的な戸寄せ処理済みです。月次データはTSV形式で，ファイルサイズは各々1.7～4.5GBです。

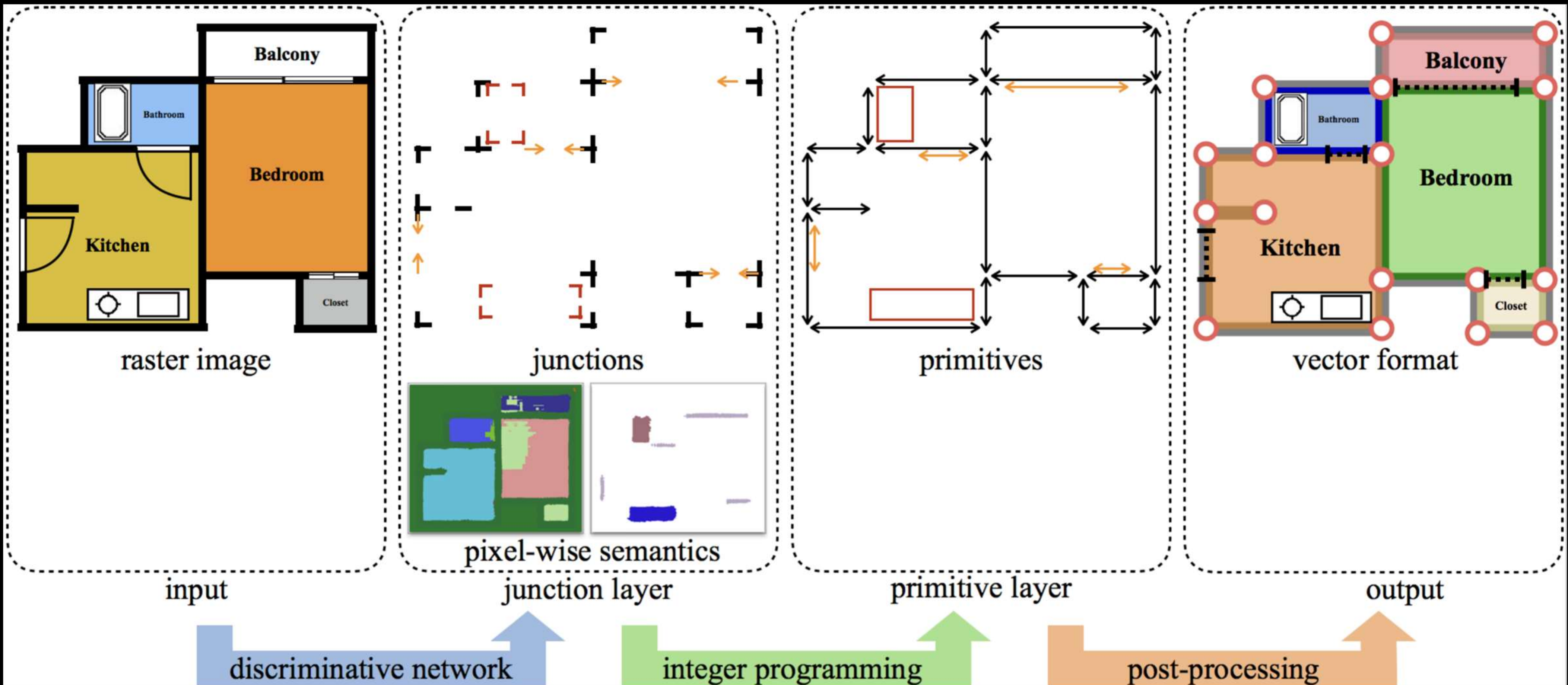
データの説明については，「LIFULLクリエイターズブログ」の2015/11/17の記事，2016/02/01の記事もご参照ください。

また本データを対象としたディープラーニング用の支援ツールキットについても同ブログの2015/12/25の記事に掲載されていますのでご参照ください。

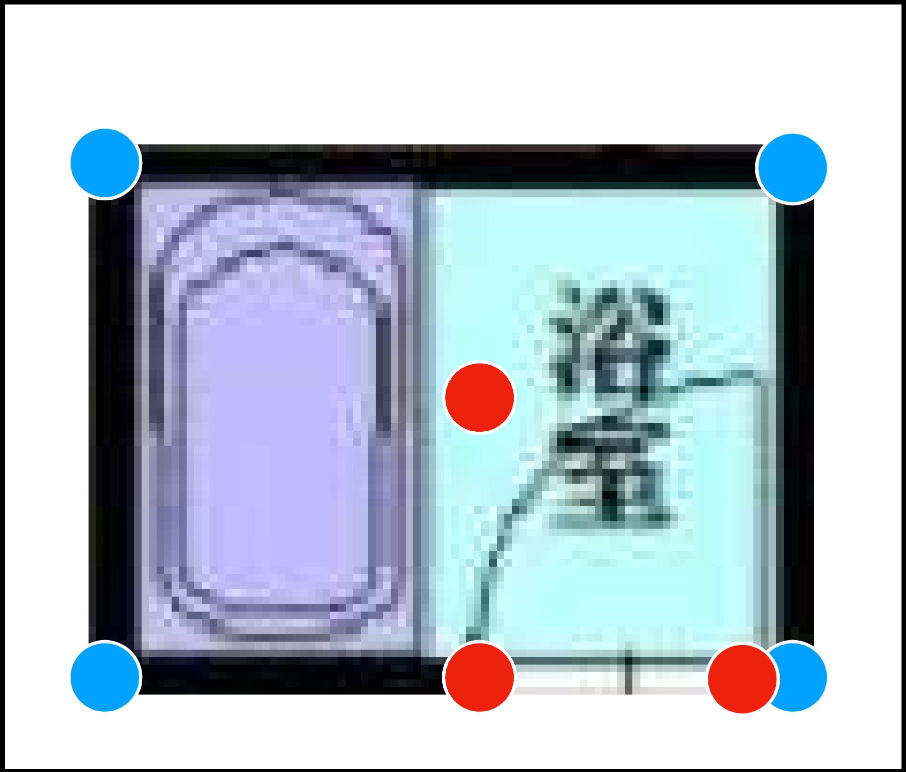
更新情報

- 利用契約を覚書形式から同意書形式に変更しました。（2019/09/12）
- 賃貸・売買物件月次データの提供を開始しました。LIFULL HOME'Sデータセットの利用者の方はダウンロードページから入手可能です。また，これに伴いこれまでのデータの名称を変更しました。（2018/12/05）
- データセットの名称が「LIFULL HOME'Sデータセット」に変更されました。（2017/04/01）
- 高精細度版の間取り図画像データの提供を開始しました。（2016/02/01）
- 「HOME'Sデータセット」の配布を開始しました。（2015/11/24）

Floorplan vectorization from scan



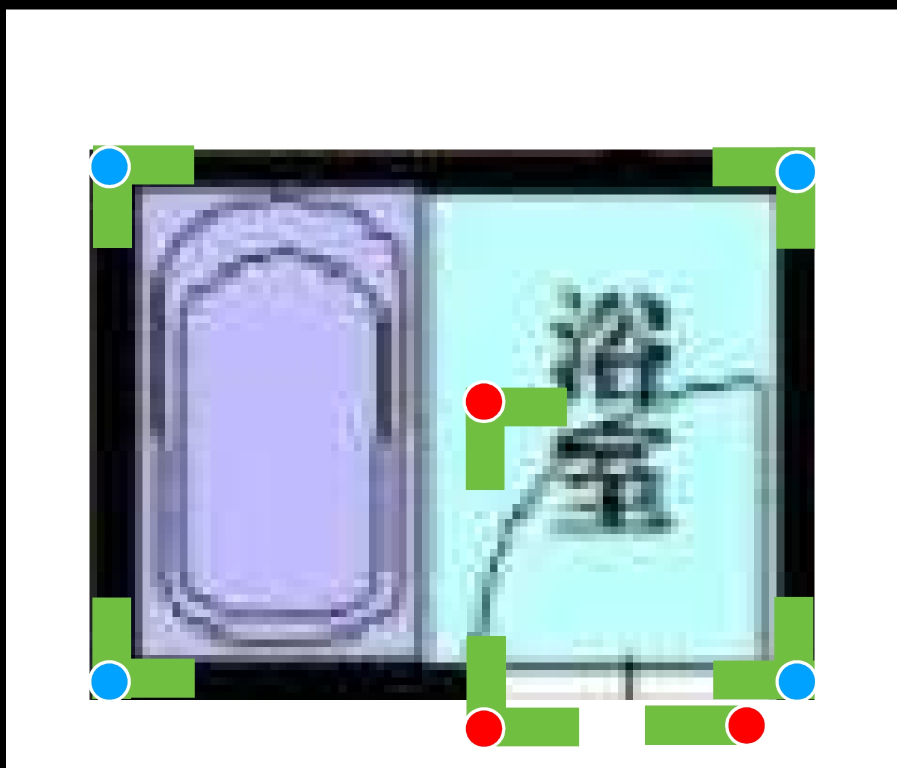
Corner detection by DNN



Wall corner

Door corner

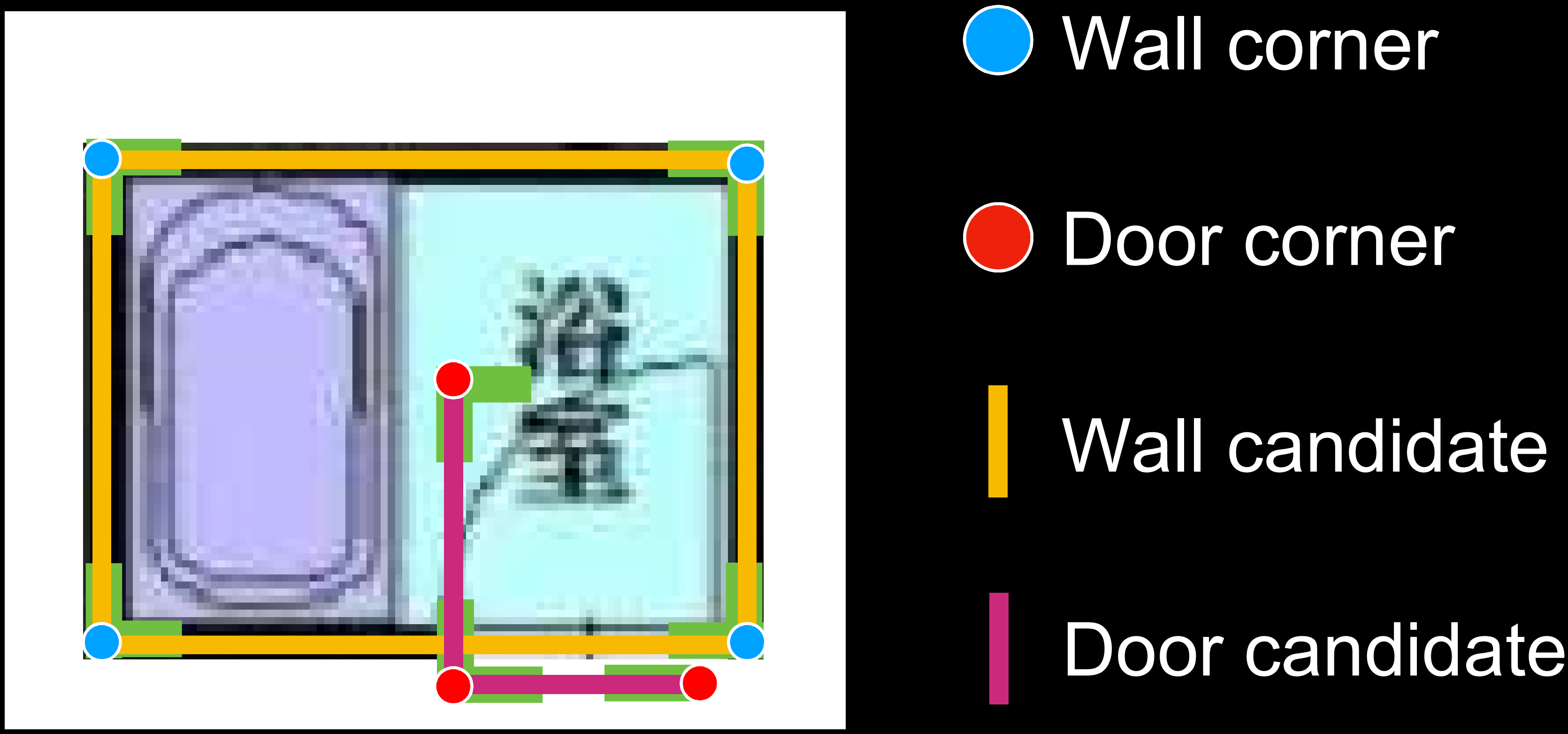
Corner detection by DNN



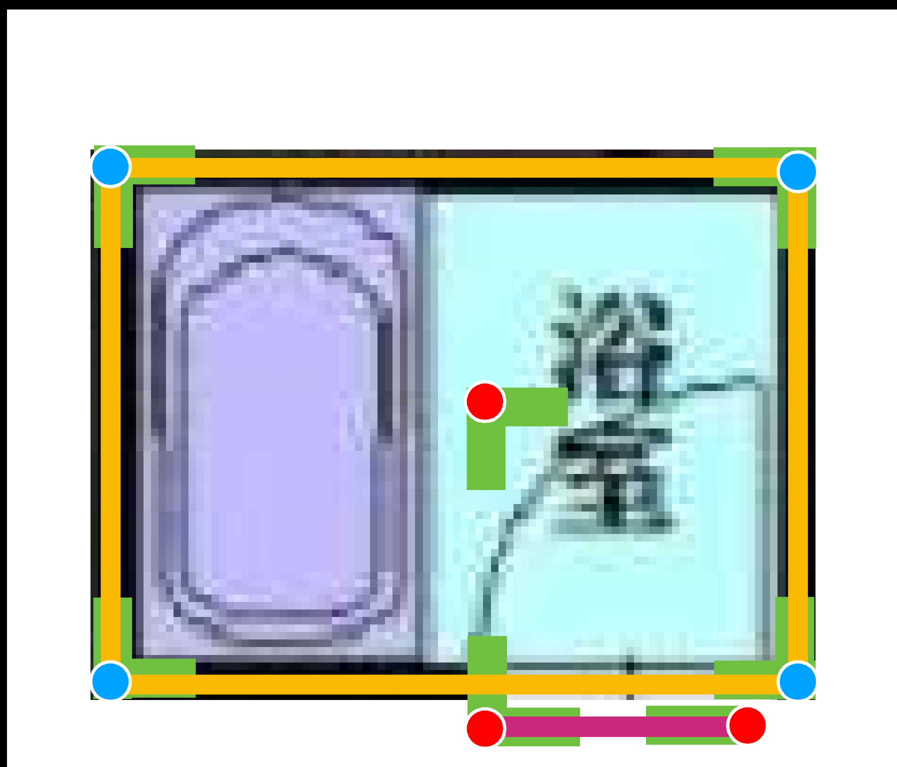
Wall corner

Door corner

Edge enumeration

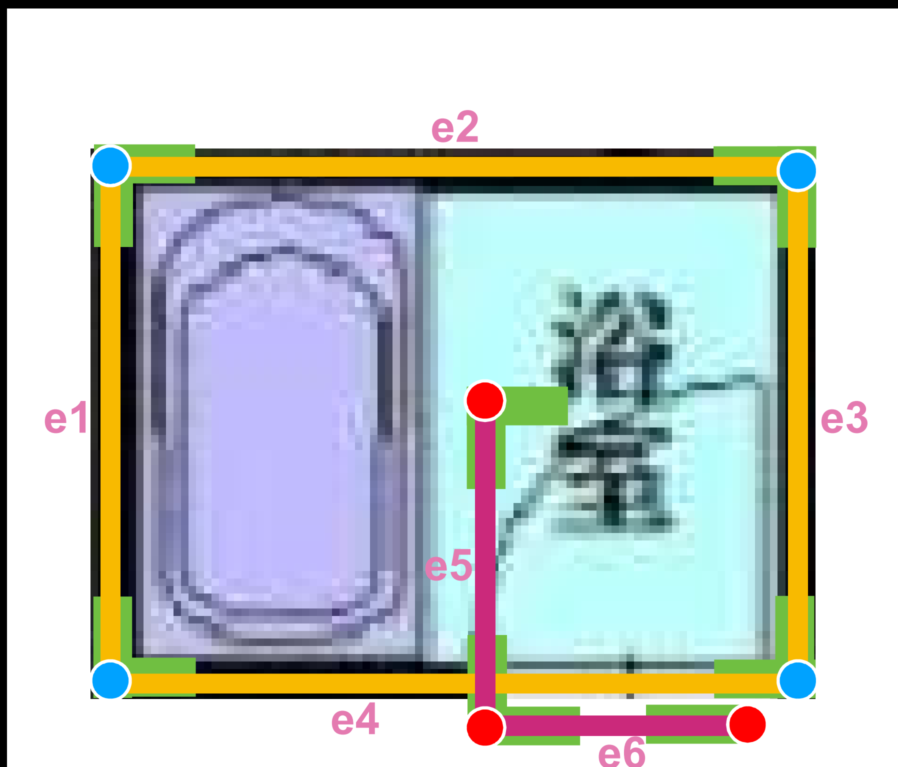


Edge selection by optimization



- Wall corner
- Door corner
- Wall candidate
- Door candidate

Edge selection by optimization

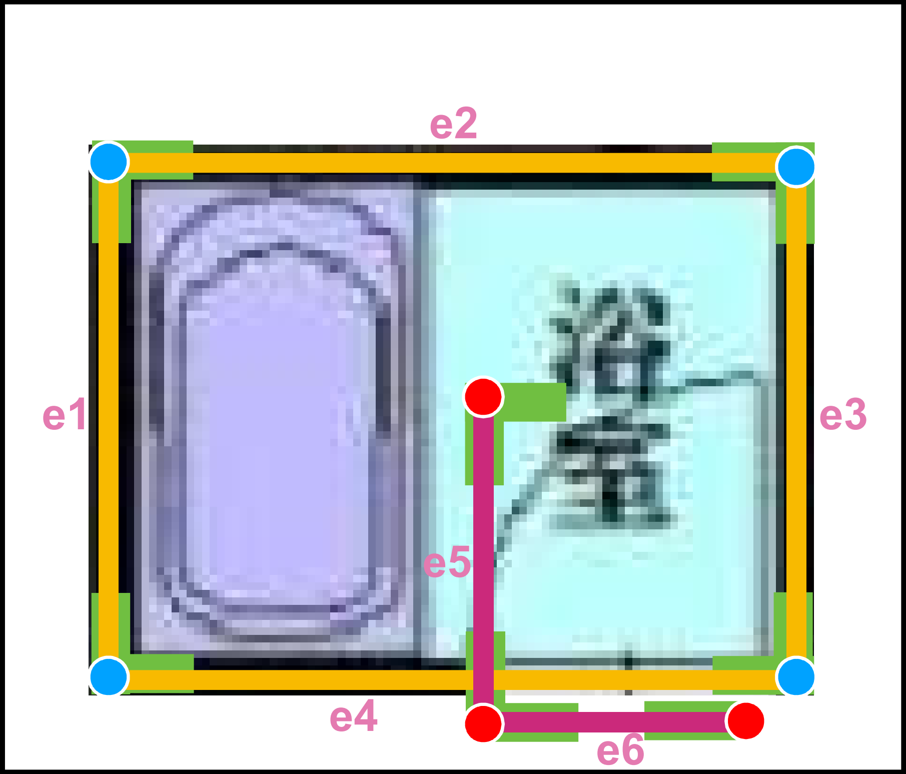


e1 – e6: Binary variables

If e1 is 1, true-edge.
Else (e1 is 0), false-edge.

We expect
e1→1 e2→1 e3→1
e4→1 e5→0 e6→1
after the optimization problem

Edge selection by optimization



e1 – e6: Binary variables

If e1 is 1, true-edge.
Else (e1 is 0), false-edge.

We expect
e1→1 e2→1 e3→1
e4→1 e5→0 e6→1
after the optimization problem

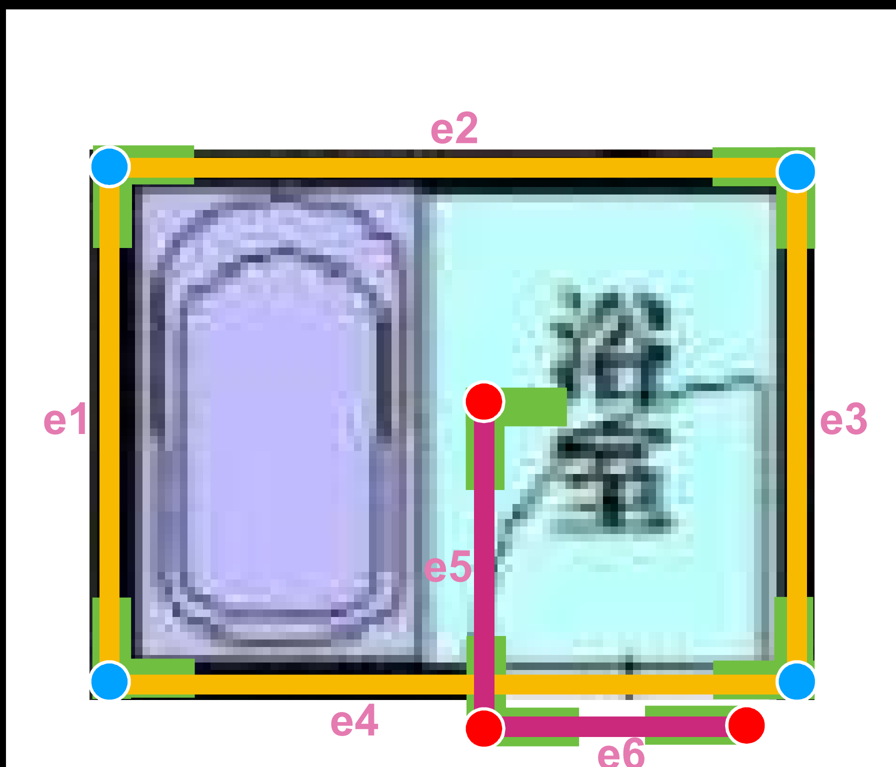
$$\max_{\{e_i\}} [e_1 + e_2 + e_3 + e_4 + e_5 + e_6]$$

Subject to

$$e_i \in \{0, 1\}$$

If we add a door e6,
there must be a door e4.

Edge selection by optimization



e1 – e6: Binary variables

If e1 is 1, true-edge.
Else (e1 is 0), false-edge.

We expect
e1→1 e2→1 e3→1
e4→1 e5→0 e6→1
after the optimization problem

$$\max_{\{e_i\}} [e_1 + e_2 + e_3 + e_4 + e_5 + e_6]$$

Subject to

$$e_i \in \{0, 1\}$$

$$e_4 \geq e_6$$

Wall junction: 26/26/26 Door: 14/14/14 Room: 11/11/11 Object: 6/6/6
Wall junction: 26/28/26 Door: 16/17/16 Room: 10/10/10 Object: 7/7/7
Wall junction: 35/35/35 Door: 16/16/16 Room: 13/13/14 Object: 5/6/6
Wall junction: 37/37/37 Door: 15/16/17 Room: 12/13/13 Object: 3/6/4
Wall junction: 57/59/60 Door: 14/16/16 Room: 13/15/18 Object: 9/15/11


Wall junction: 22/24/22 Door: 11/11/11 Room: 9/9/9 Object: 6/6/6
Wall junction: 20/20/20 Door: 8/9/9 Room: 6/7/7 Object: 8/9/9
Wall junction: 20/22/20 Door: 8/8/8 Room: 7/8/8 Object: 7/9/8
Wall junction: 22/24/22 Door: 10/10/10 Room: 9/9/9 Object: 6/6/6
Wall junction: 29/30/30 Door: 15/15/15 Room: 10/11/11 Object: 6/6/6
Wall junction: 18/18/18 Door: 8/8/8 Room: 7/7/7 Object: 5/6/6
Wall junction: 30/34/32 Door: 7/7/7 Room: 7/9/10 Object: 8/10/9
Wall junction: 16/18/18 Door: 6/6/6 Room: 6/7/7 Object: 4/4/4
Wall junction: 26/26/26 Door: 14/14/14 Room: 11/11/11 Object: 7/7/7
Wall junction: 21/21/21 Door: 7/7/9 Room: 6/7/7 Object: 5/5/5
Wall junction: 23/23/23 Door: 9/11/12 Room: 9/10/10 Object: 7/7/7
Wall junction: 24/24/24 Door: 15/15/15 Room: 10/10/10 Object: 5/5/5
Wall junction: 31/31/31 Door: 13/17/15 Room: 13/13/13 Object: 5/5/6
Wall junction: 19/19/19 Door: 7/7/7 Room: 7/7/7 Object: 4/4/4
Wall junction: 33/33/33 Door: 13/14/14 Room: 11/11/13 Object: 6/8/7

Method	Wall Junction		Opening		Icon		Room	
	Acc.	Recall	Acc.	Recall	Acc.	Recall	Acc.	Recall
Ahmed *et al*. [6]	74.9	57.5	61.3	48.7	N/A	N/A	N/A	N/A
Ours (without IP)	70.7	95.1	67.9	91.4	22.3	77.4	80.9	78.5
Ours (without mutual exclusion constraints)	92.8	91.7	68.5	91.1	22.0	76.2	82.8	87.5
Ours (without loop constraints)	94.2	91.5	91.9	90.2	84.3	75.0	82.5	88.2
Ours (without opening constraints)	94.6	91.7	91.7	90.1	84.0	74.8	84.3	88.3
Ours (with full IP)	94.7	91.7	91.9	90.2	84.0	74.6	84.5	88.4

Floorplan vectorization from scan

Bottom-up

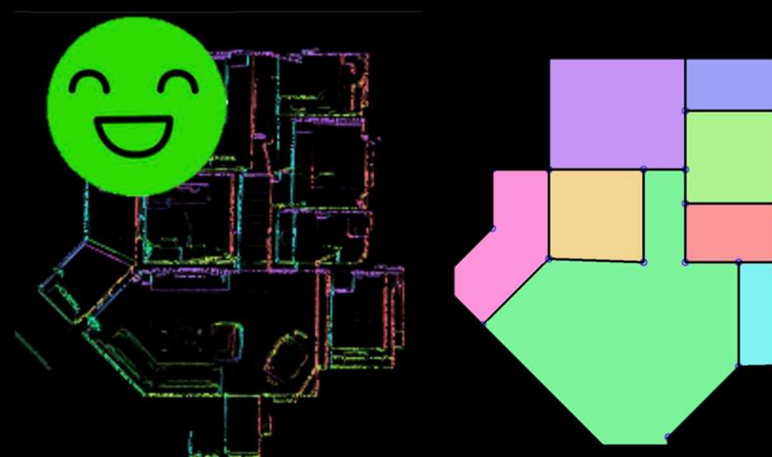
1. Corners by DNN
2. Edges/regions by optimization

ICCV 2017

Floorplan reconstruction from 3D points

Top-down

1. Regions by DNN
2. Edges/corners by optimization



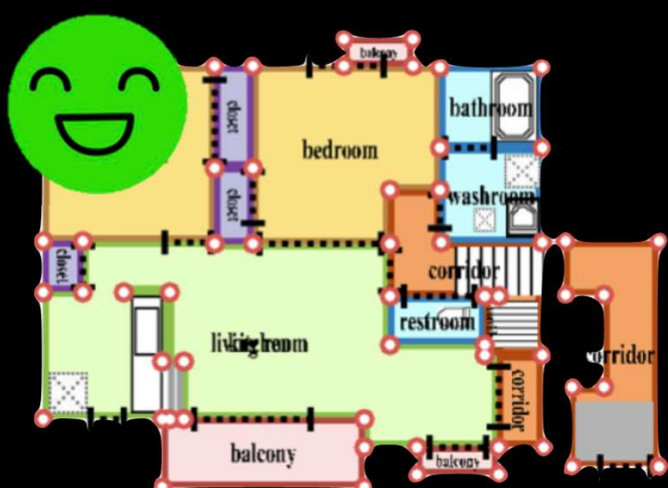
ECCV 2018/ICCV 2019

Floorplan vectorization from scan

Floorplan reconstruction from 3D points

Bottom-up

1. Corners by DNN
2. Edges/regions by optimization

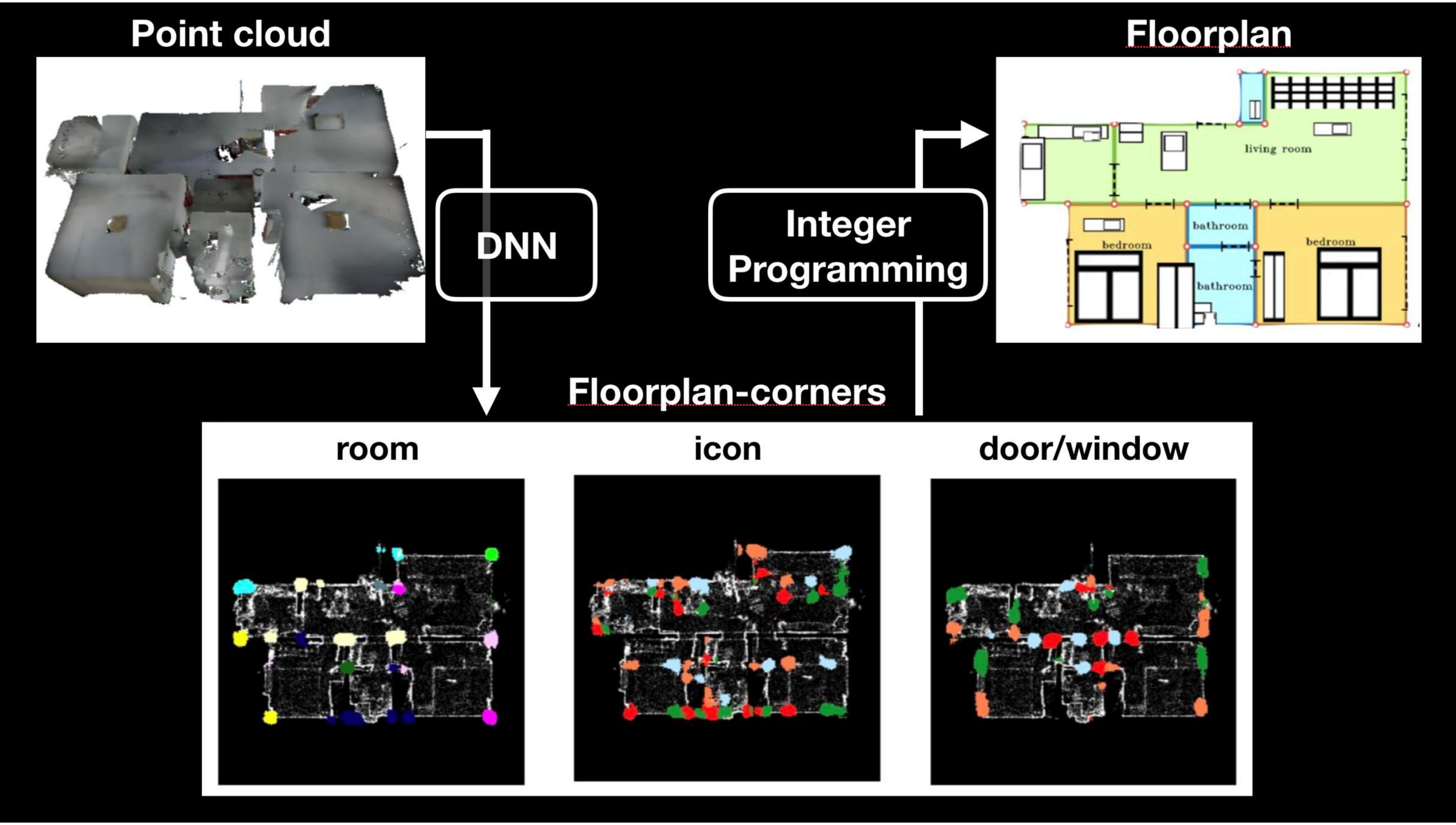


ICCV 2017

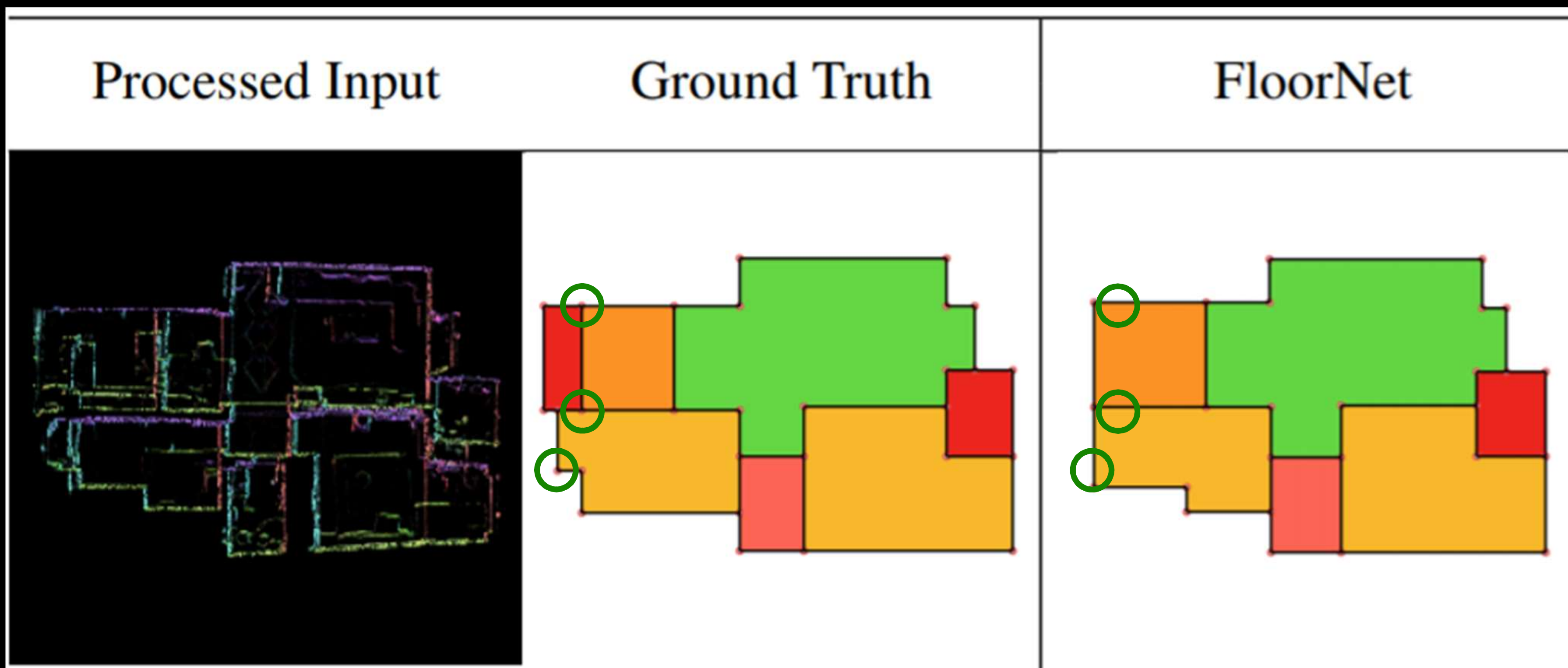
Top-down

1. Regions by DNN
2. Edges/corners by optimization

ECCV 2018/ICCV 2019

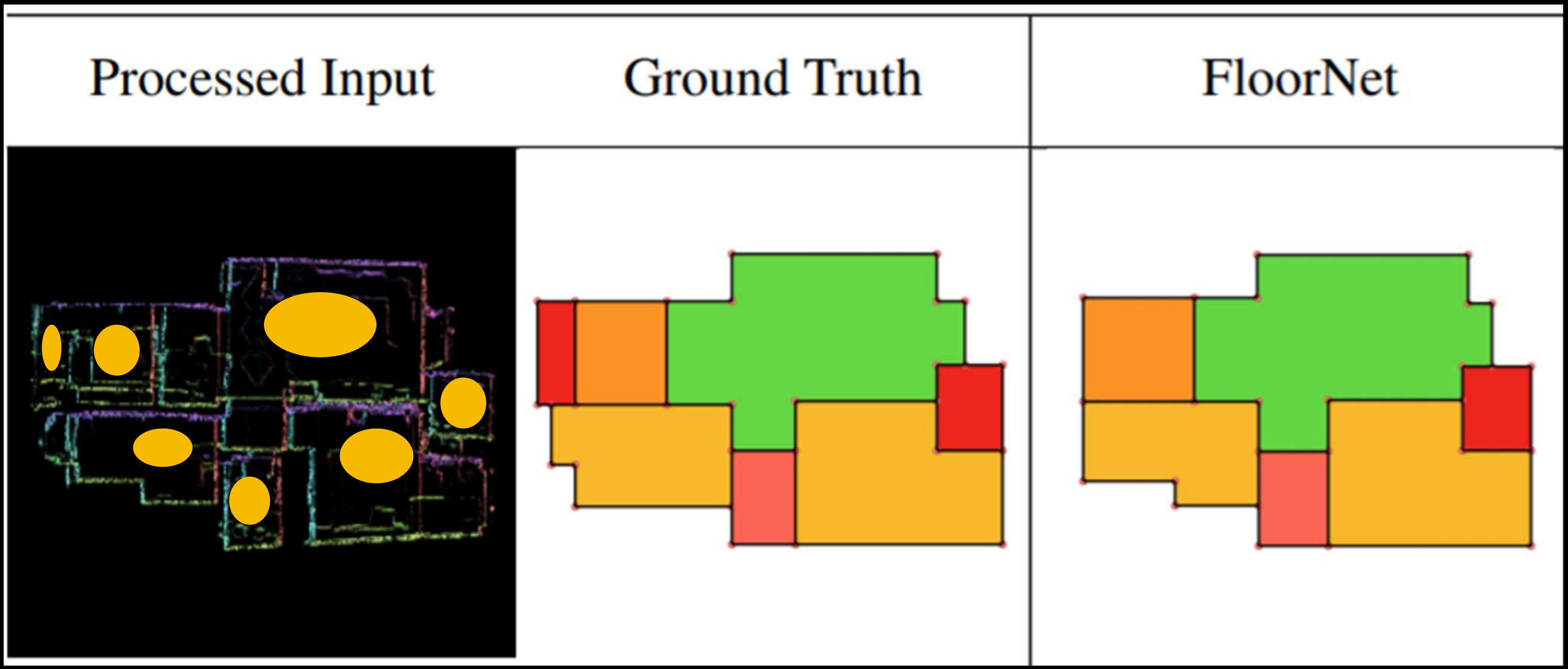

Point cloud
Floorplan
DNN
Integer Programming
living room
bathroom
bedroom
bathroom
bedroom
Floorplan-corners
room
icon
door/window

Issues of bottom-up



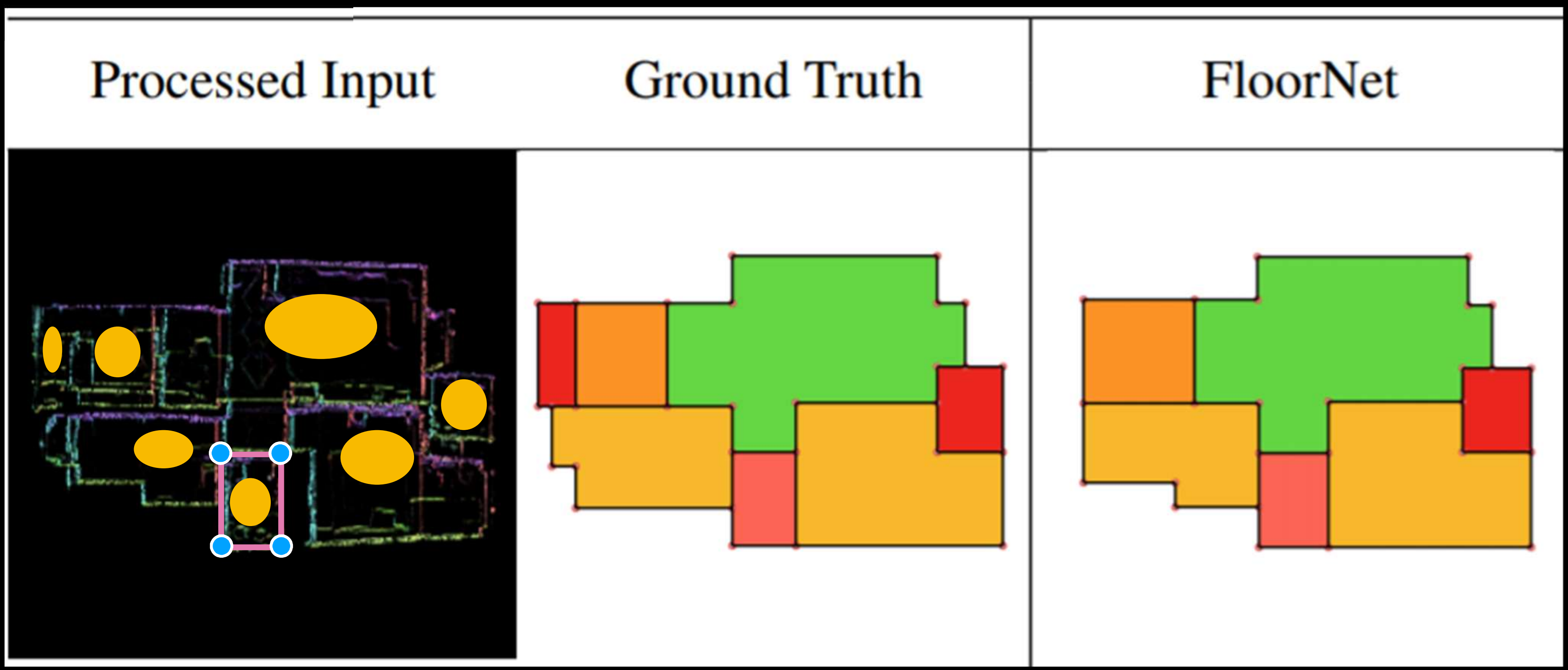
Cannot miss a single corner

Issues of bottom-up



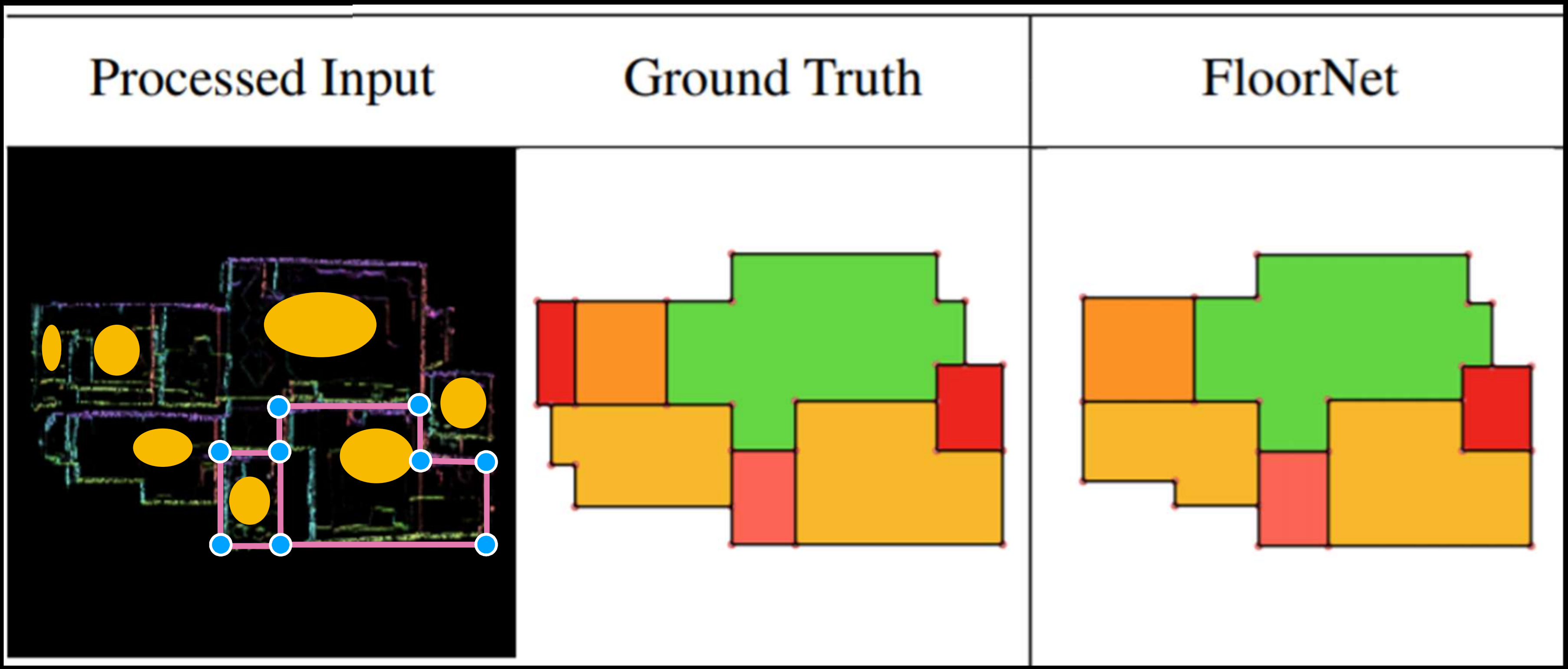
Much easier to detect regions

Top-down approach



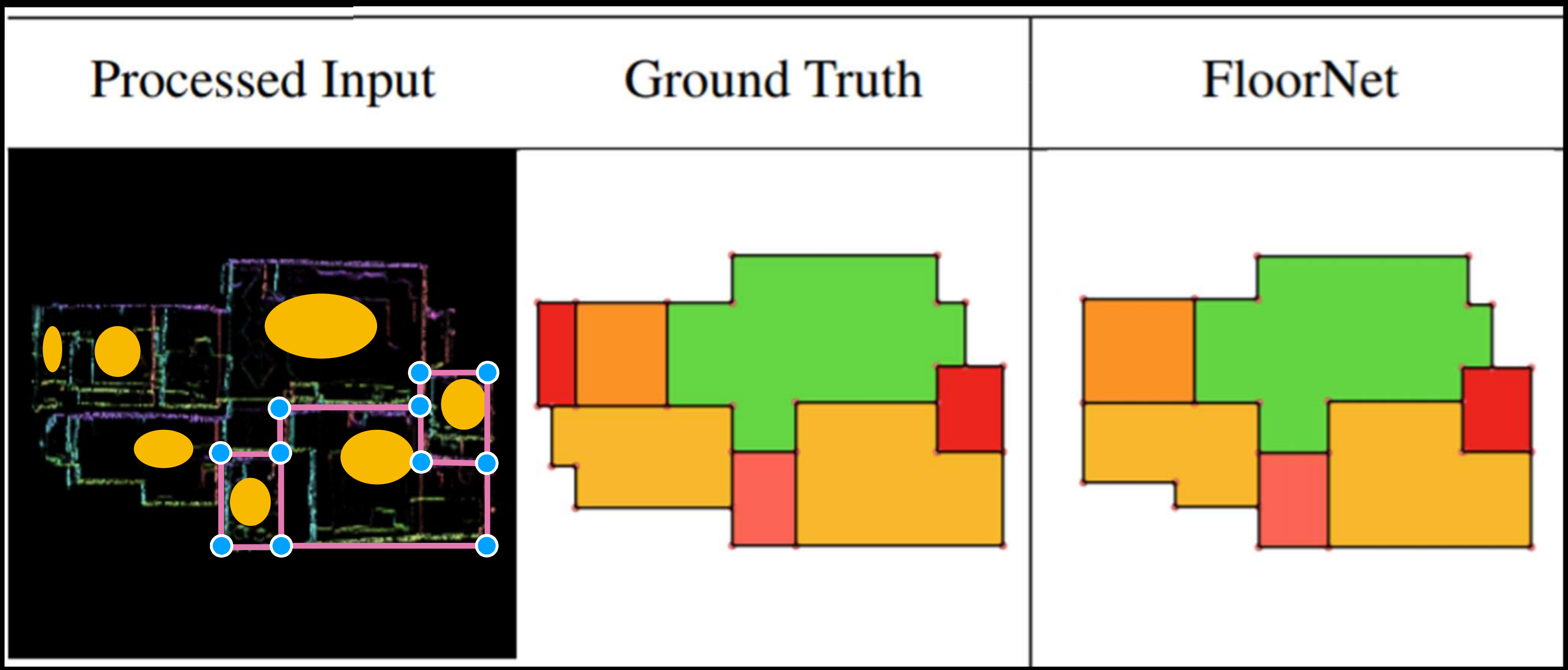
Given a region, solve for its boundary

Top-down approach



Given a region, solve for its boundary

Top-down approach



Given a region, solve for its boundary

Optimization formulation

1. Shortest path problem reduction

Our objective has three factors: intra-room data term, inter-room consistency term, and model complexity term.

• The data-term $E_{data}(L_i)$ is pixel-wise penalties summed over pixels along the loops, and hence, the reduction to the shortest path cost is straightforward for each loop. More concretely, every corner of a room is shared by two edges, thus contributes half of its cost to one edge:

$$\sum_{p \in \mathbb{C}(e)} \frac{\lambda_1}{2} E^{\mathcal{C}}_{data}(p).$$

The edge and interior penalties are summed over pixels along each edge without any changes:

$$\sum_{p \in \mathbb{E}(e)} \left[\lambda_2 E^{\mathcal{E}}_{data}(p) + \lambda_3 E^{\mathcal{I}}_{data}(p)\right].$$

• The model complexity $E_{model}(L_i)$ is a constant penalized for each edge, which is simply added to the weight of an edge:

$$\lambda_6.$$

• The consistency term $E_{consis}(\mathcal{L})$ is the number of pixels that are used by the corners (or edges) of all the loops. In the room-wise coordinate descent optimization where we fix the loops of all the other rooms, this term can be reduced to the shortest path cost. Without loss of regularity, suppose we are optimizing L_1. If a pixel p of edge e in L_1 is already used by other rooms, this pixel is imposed penalties regardless of L_i. Therefore, the shortest path problem considers only pixels that are not used by any other rooms:

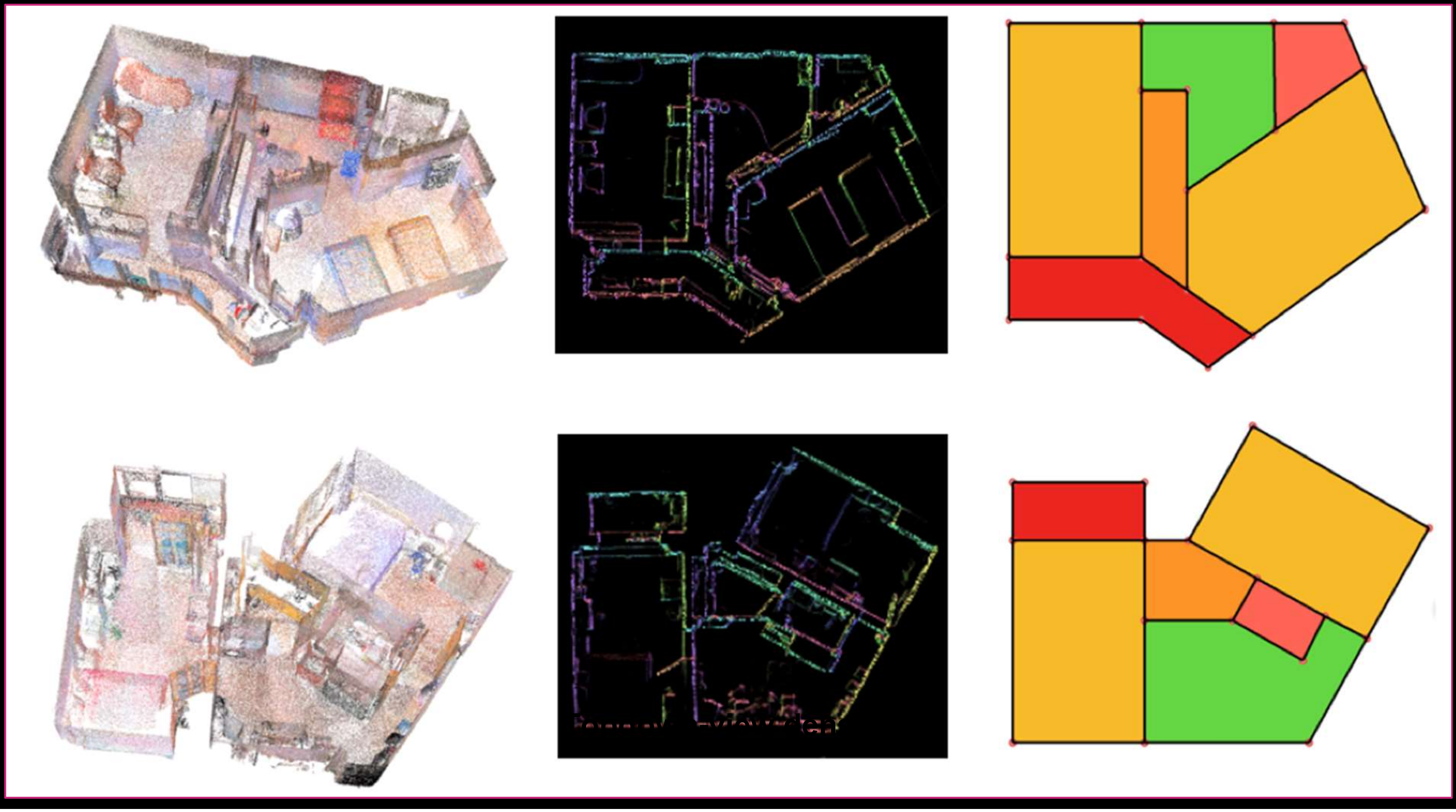
$$\sum_{p \in \mathbb{C}(e)} \lambda_4 (1 - \mathbf{1}_{\mathcal{C}}(p, \mathcal{L} \setminus \{L_1\})) +$$
$$\sum_{p \in \mathbb{E}(e)} \lambda_5 (1 - \mathbf{1}_{\mathcal{E}}(p, \mathcal{L} \setminus \{L_1\})).$$

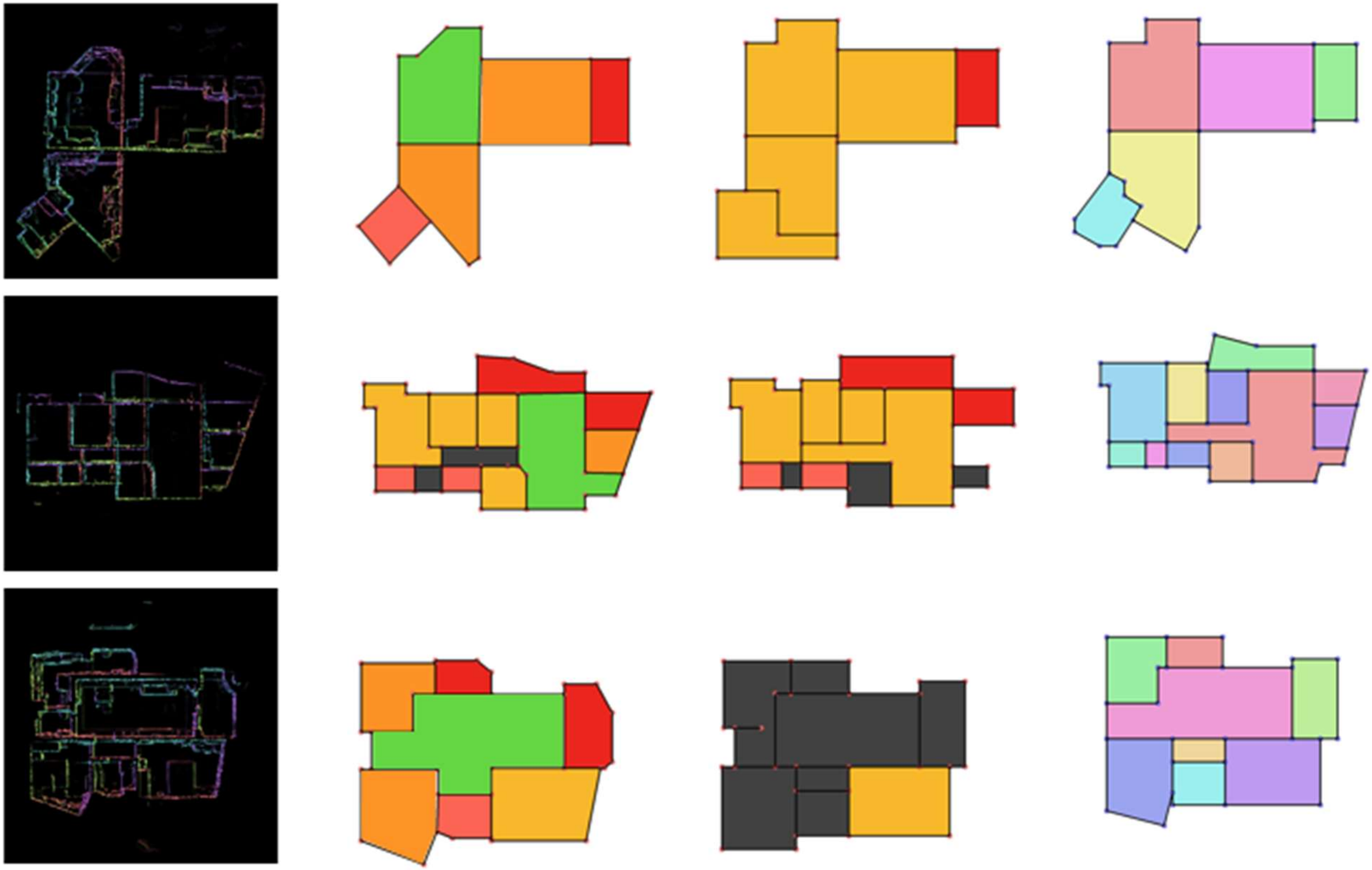
$\mathbb{C}(e)$ is the two pixels at the two end-points of an edge (e). $\mathbb{E}(e)$ is a set of pixels along the edge containing the corners. In our implementation, we obtain $\mathbb{E}(e)$ using Bresenham's line algorithm.

In summary, a single room-wise coordinate descent optimization step is reduced to a shortest path problem, where the weight of an edge is defined as follows.

$$\begin{aligned}
&\sum_{p \in \mathbb{C}(e)} \frac{\lambda_1}{2} E^{\mathcal{C}}_{data}(p) \quad + \\
&\sum_{p \in \mathbb{E}(e)} \left[\lambda_2 E^{\mathcal{E}}_{data}(p) + \lambda_3 E^{\mathcal{I}}_{data}(p)\right] \quad + \\
&\sum_{p \in \mathbb{C}(e)} \lambda_4 (1 - \mathbf{1}_{\mathcal{C}}(p, \mathcal{L} \setminus \{L_1\})) \quad + \\
&\sum_{p \in \mathbb{E}(e)} \lambda_5 (1 - \mathbf{1}_{\mathcal{E}}(p, \mathcal{L} \setminus \{L_1\})) \quad + \quad \lambda_6.
\end{aligned}$$

527 panorama RGBD scans with floorplan annotations from Beike (https://www.ke.com)





Top down point density | Ground-truth | FloorNet (Bottom-up) | Ours (Top-down)

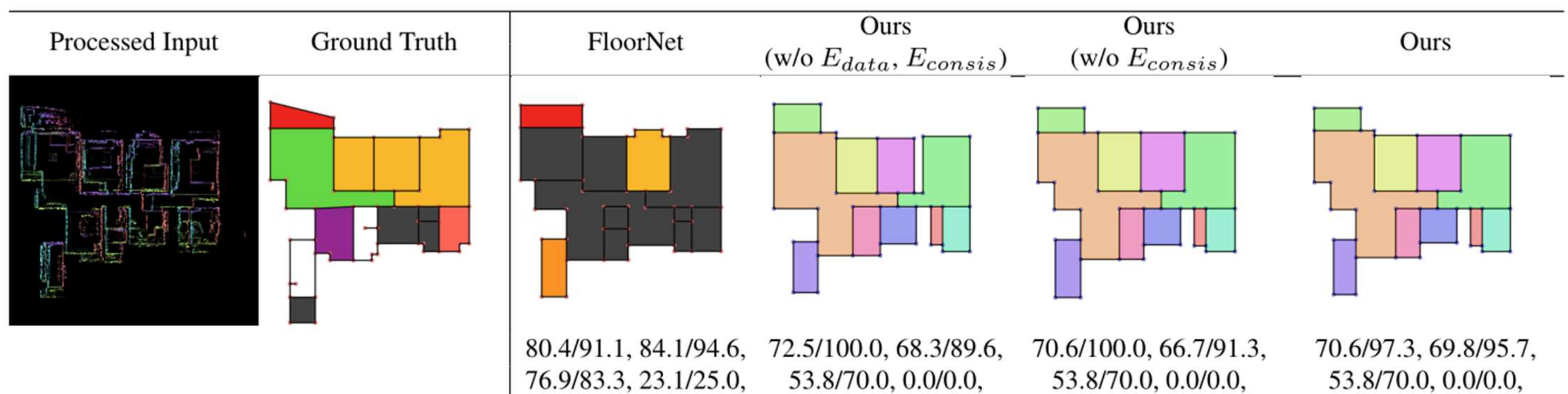


Table 1. The main quantitative evaluation results. The colors cyan, orange, magenta represent the top three entries.

Method	Corner		Edge		Room		Room++	
	Prec.	Recall	Prec.	Recall	Prec.	Recall	Prec.	Recall
FloorNet [20]	95.0	76.6	94.8	76.8	81.2	72.1	42.3	37.5
Ours (w/o E_{data}, E_{consis})	84.4	80.4	82.3	79.8	75.1	61.3	23.3	22.0
Ours (w/o E_{consis})	93.9	82.3	89.2	81.2	83.8	81.7	49.4	48.5
Ours (1st-round coordinate descent)	94.6	82.8	89.4	81.7	83.9	81.8	49.5	48.7
Ours (2nd-round coordinate descent)	95.1	82.2	90.2	81.1	84.7	83.0	51.4	50.4

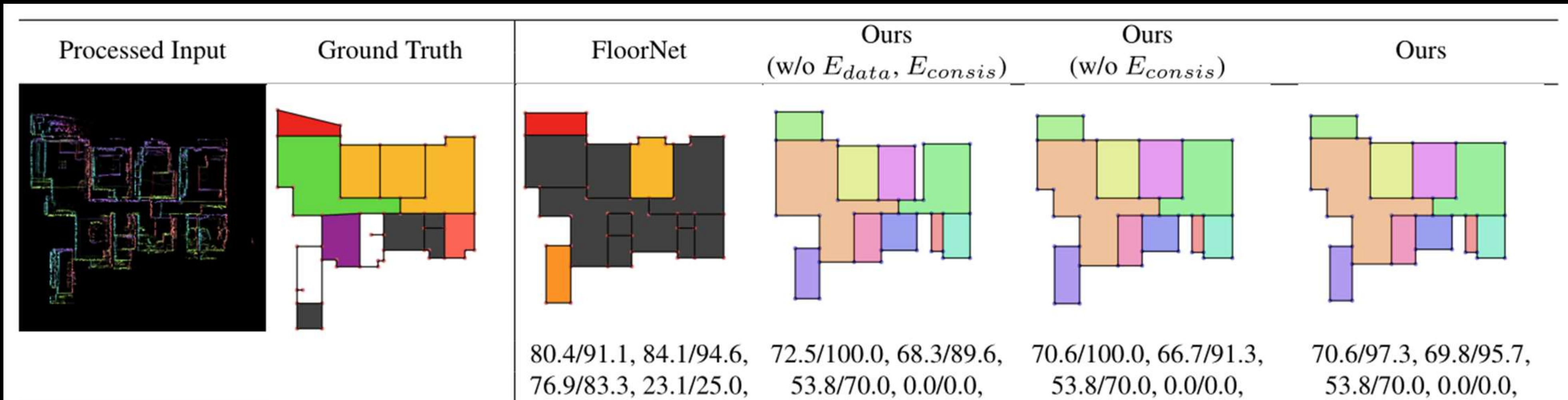
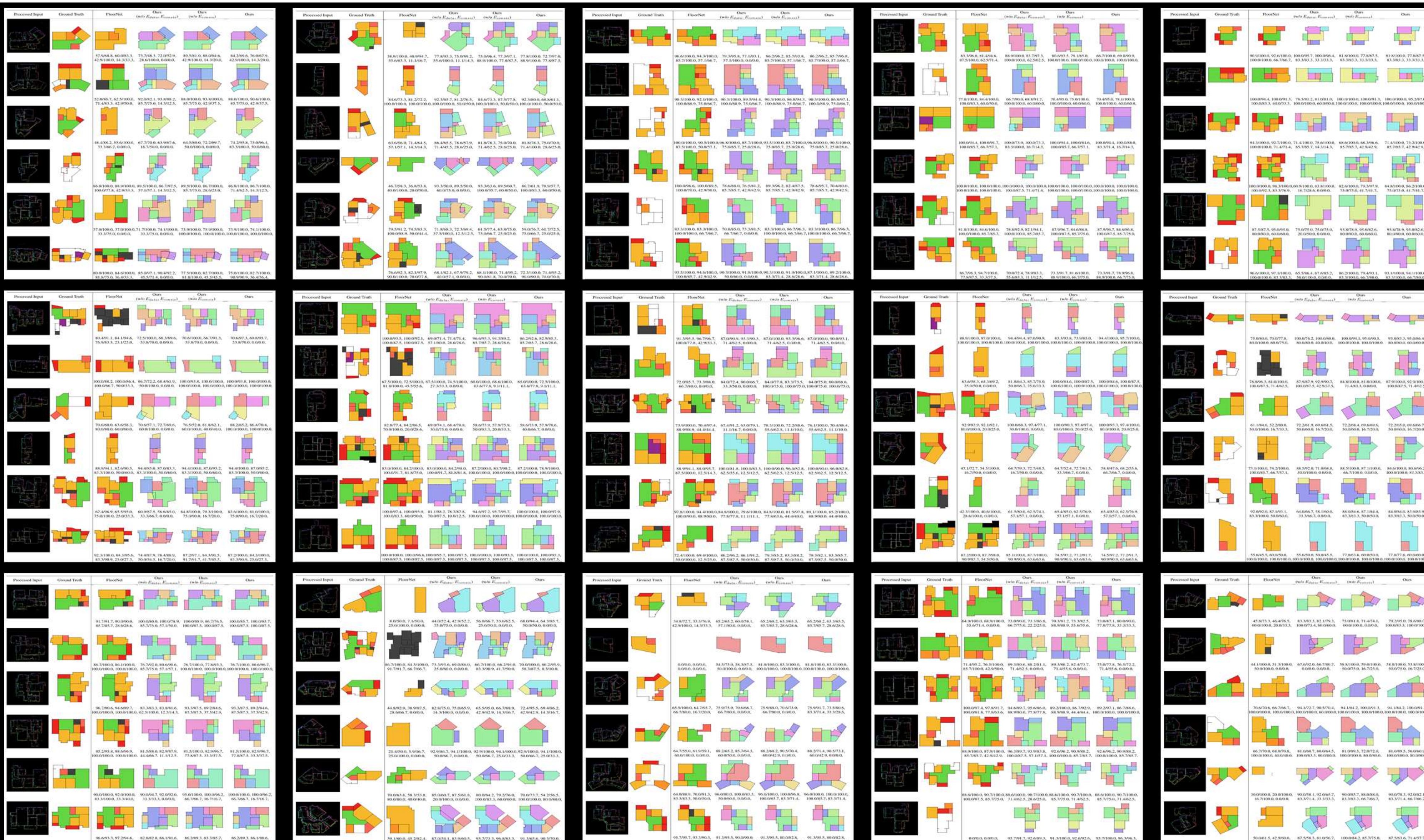
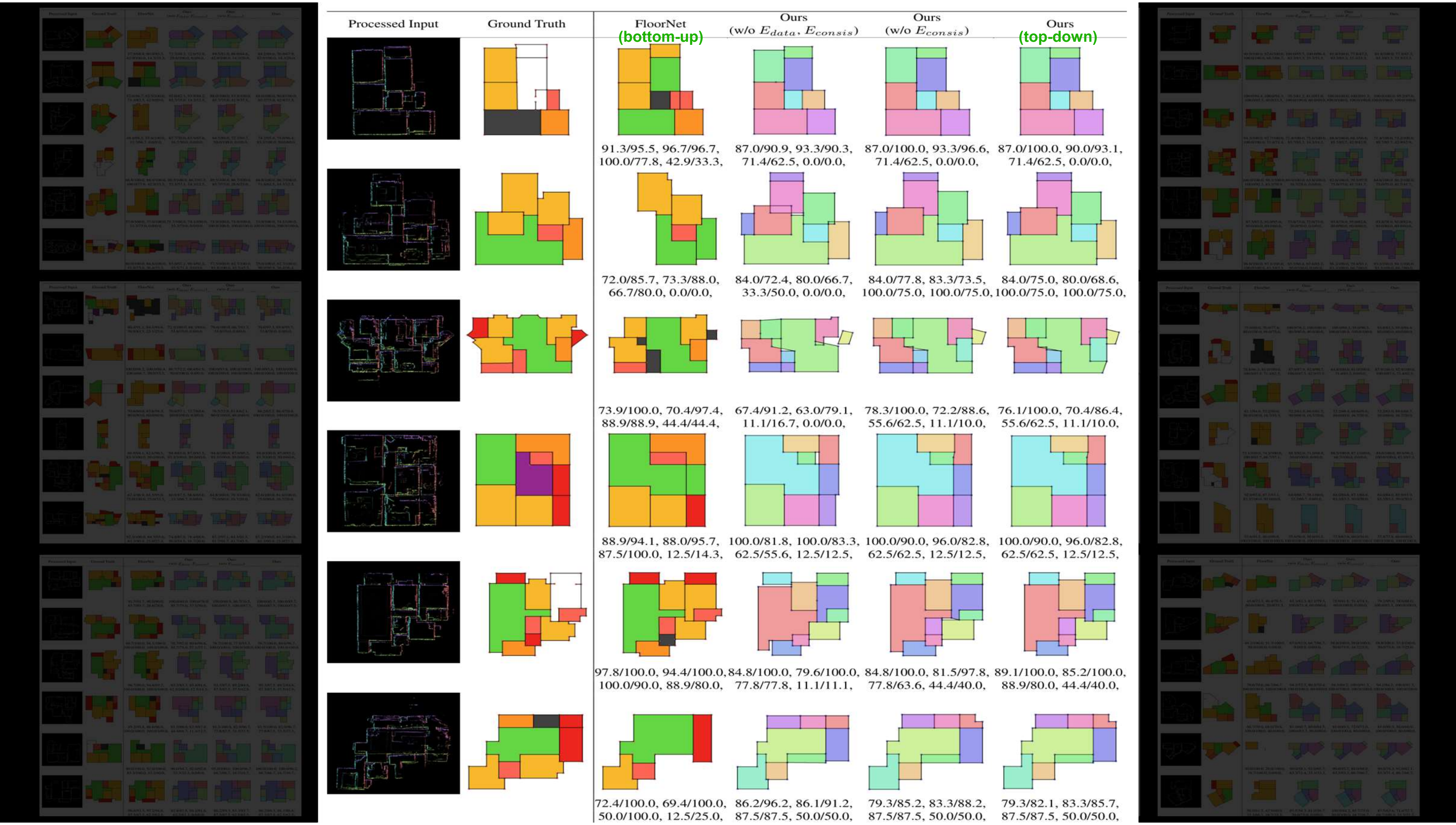


Table 1. The main quantitative evaluation results. The colors cyan, orange, magenta represent the top three entries.

Method	Corner		Edge		Room		Room++	
	Prec.	Recall	Prec.	Recall	Prec.	Recall	Prec.	Recall
FloorNet [20] **(bottom-up)**	95.0	76.6	94.8	76.8	81.2	72.1	42.3	37.5
Ours (w/o E_{data}, E_{consis})	84.4	80.4	82.3	79.8	75.1	61.3	23.3	22.0
Ours (w/o E_{consis})	93.9	82.3	89.2	81.2	83.8	81.7	49.4	48.5
Ours (1st-round coordinate descent)	94.6	82.8	89.4	81.7	83.9	81.8	49.5	48.7
Ours (2nd-round coordinate descent) **(top-down)**	95.1	82.2	90.2	81.1	84.7	83.0	51.4	50.4


Processed Input
Ground Truth
FloorNet
Ours


Processed Input
Ground Truth
FloorNet
(bottom-up)
Ours
(w/o E_{data}, E_{consis})
Ours
(w/o E_{consis})
Ours
(top-down)
91.3/95.5, 96.7/96.7,
100.0/77.8, 42.9/33.3,
87.0/90.9, 93.3/90.3,
71.4/62.5, 0.0/0.0,
87.0/100.0, 93.3/96.6,
71.4/62.5, 0.0/0.0,
87.0/100.0, 90.0/93.1,
71.4/62.5, 0.0/0.0,
72.0/85.7, 73.3/88.0,
66.7/80.0, 0.0/0.0,
84.0/72.4, 80.0/66.7,
33.3/50.0, 0.0/0.0,
84.0/77.8, 83.3/73.5,
100.0/75.0, 100.0/75.0,
84.0/75.0, 80.0/68.6,
100.0/75.0, 100.0/75.0,
73.9/100.0, 70.4/97.4,
88.9/88.9, 44.4/44.4,
67.4/91.2, 63.0/79.1,
11.1/16.7, 0.0/0.0,
78.3/100.0, 72.2/88.6,
55.6/62.5, 11.1/10.0,
76.1/100.0, 70.4/86.4,
55.6/62.5, 11.1/10.0,
88.9/94.1, 88.0/95.7,
87.5/100.0, 12.5/14.3,
100.0/81.8, 100.0/83.3,
62.5/55.6, 12.5/12.5,
100.0/90.0, 96.0/82.8,
62.5/62.5, 12.5/12.5,
100.0/90.0, 96.0/82.8,
62.5/62.5, 12.5/12.5,
97.8/100.0, 94.4/100.0,
100.0/90.0, 88.9/80.0,
84.8/100.0, 79.6/100.0,
77.8/77.8, 11.1/11.1,
84.8/100.0, 81.5/97.8,
77.8/63.6, 44.4/40.0,
89.1/100.0, 85.2/100.0,
88.9/80.0, 44.4/40.0,
72.4/100.0, 69.4/100.0,
50.0/100.0, 12.5/25.0,
86.2/96.2, 86.1/91.2,
87.5/87.5, 50.0/50.0,
79.3/85.2, 83.3/88.2,
87.5/87.5, 50.0/50.0,
79.3/82.1, 83.3/85.7,
87.5/87.5, 50.0/50.0,

Bottom-up → **Top-down**

Heuristics

ECCV 2012

- Detect high-level primitives.
- DNN does not help structured modeling

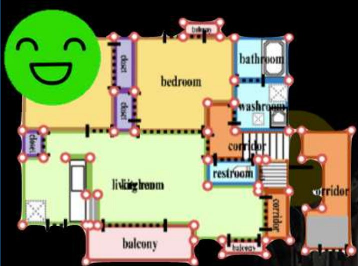
CVPR 2009

CVPR 2014

ICCV 2015

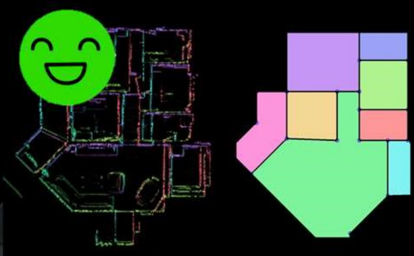
- Corner detection
  as input is clean image
- Complex optimization

- Region detection
  as input is noisy points
- Very complex optimization



ICCV 2017

CVPR 2018/CVPR 2019


ECCV 2018/ICCV 2019

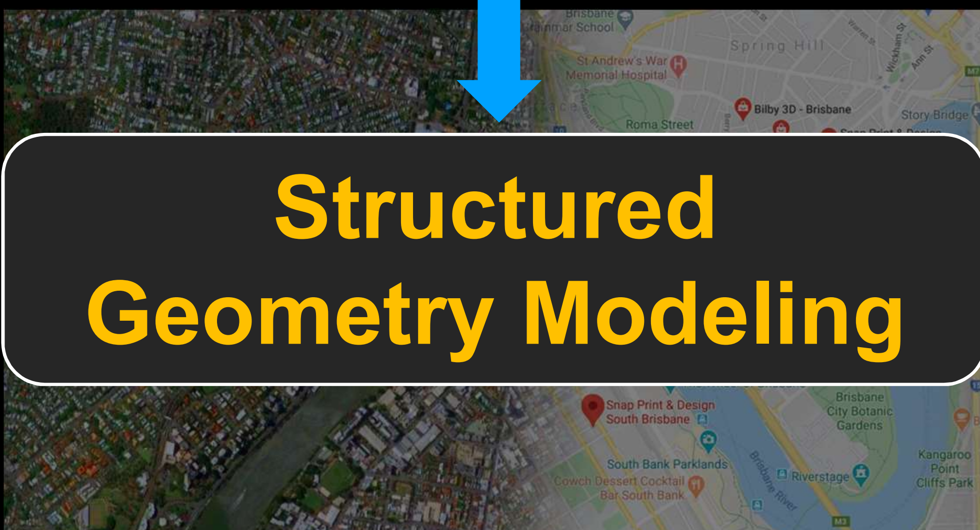
Data-driven

CVPR 2020

ECCV 2018

2 Fundamental Technologies

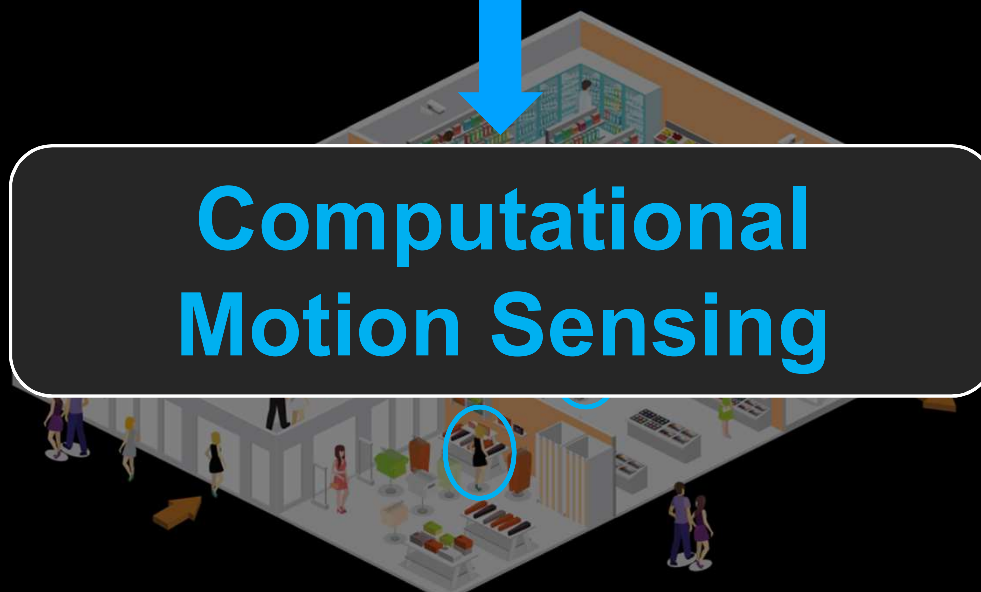
Mapping
Content Creation



Structured Geometry Modeling

[https://towardsdatascience.com]

Localization
Content Selection



Computational Motion Sensing

Navigation, Mobile-Apps, AR-Games, Business-AR