3D City Models for

Digital Maps and Navigation

M.Sc. Andreas Wichmann

Institute of Geodesy and Geoinformation Science
Technische Universität Berlin

3D City Models

Source: http://www.dresden.de

Source: https://www.karlsruhe.de

3D City Models for Digital Maps

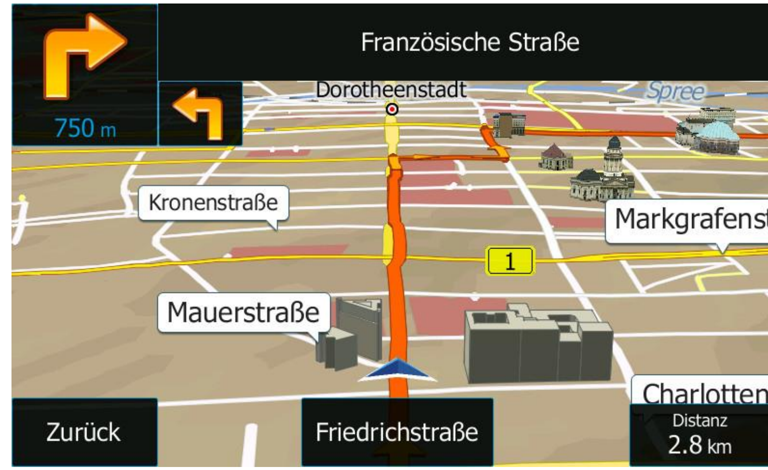
Source: https://www.google.de

3D City Models for Digital Maps

Google Maps

Apple Maps

3D City Models for Navigation



Source: http://www.blaupunkt.com

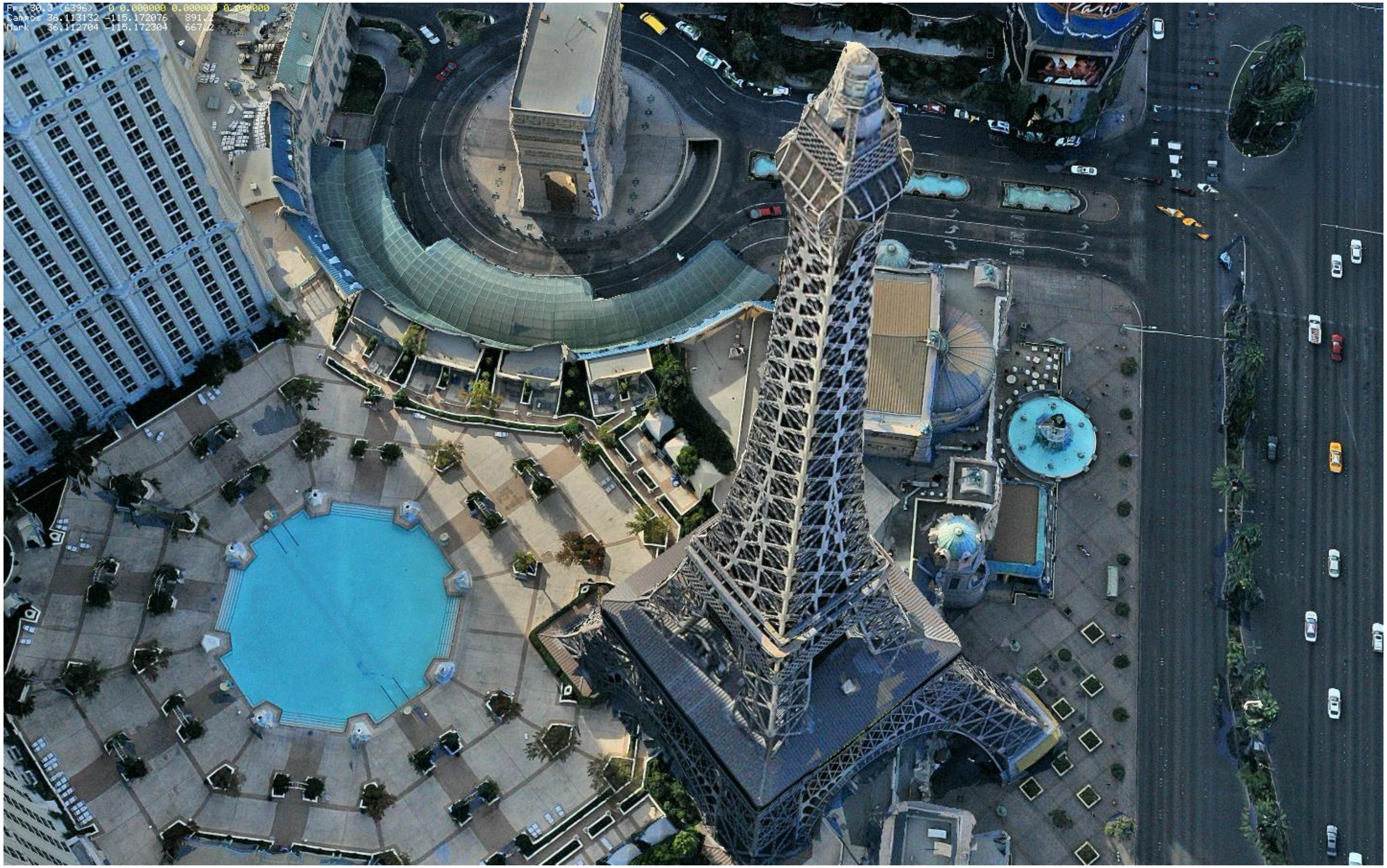
Source: https://www.tomtom.com

Source: https://www.garmin.com

3D City Models for Navigation

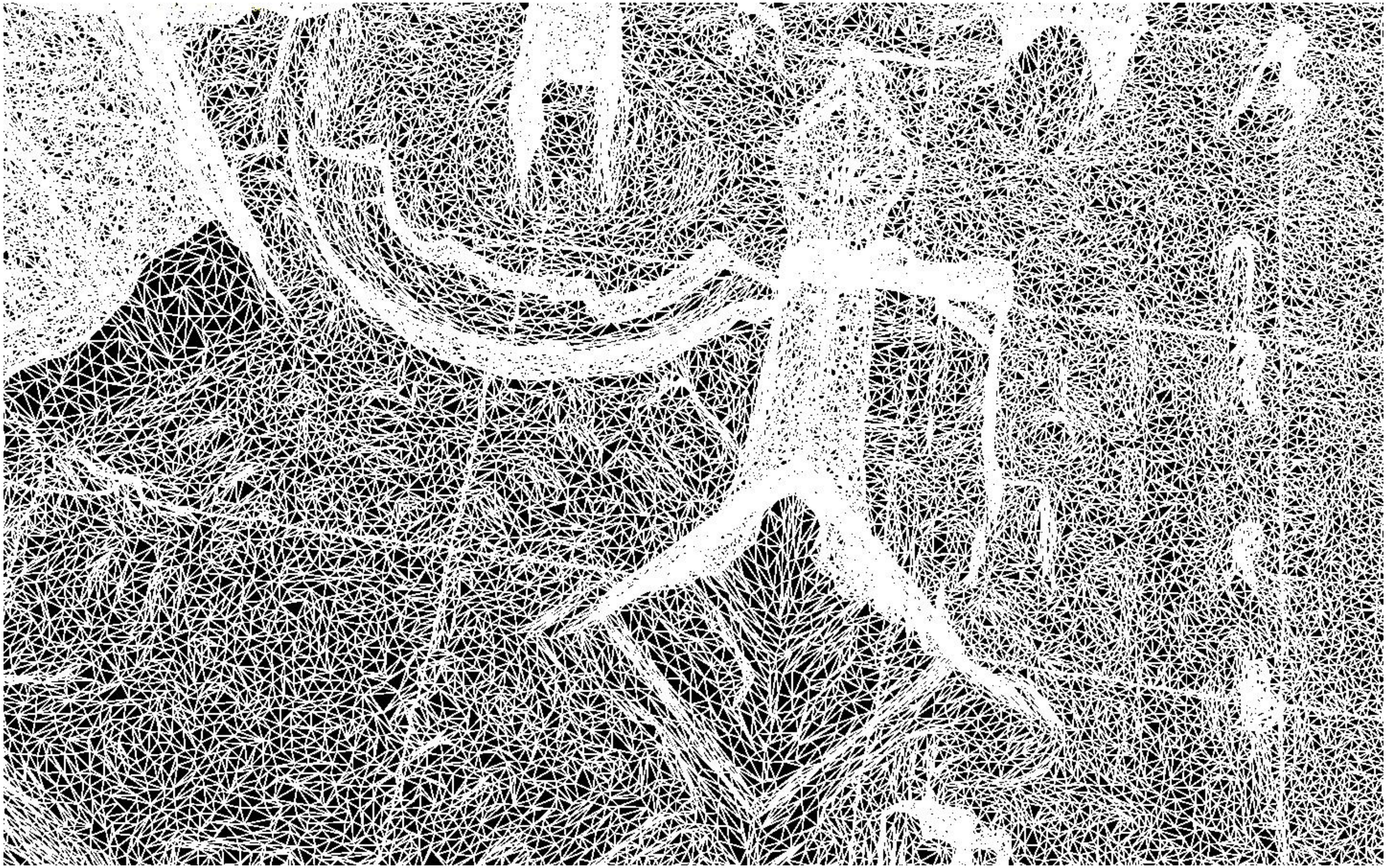
Source: http://osmbuildings.org

3D City Models for Digital Maps



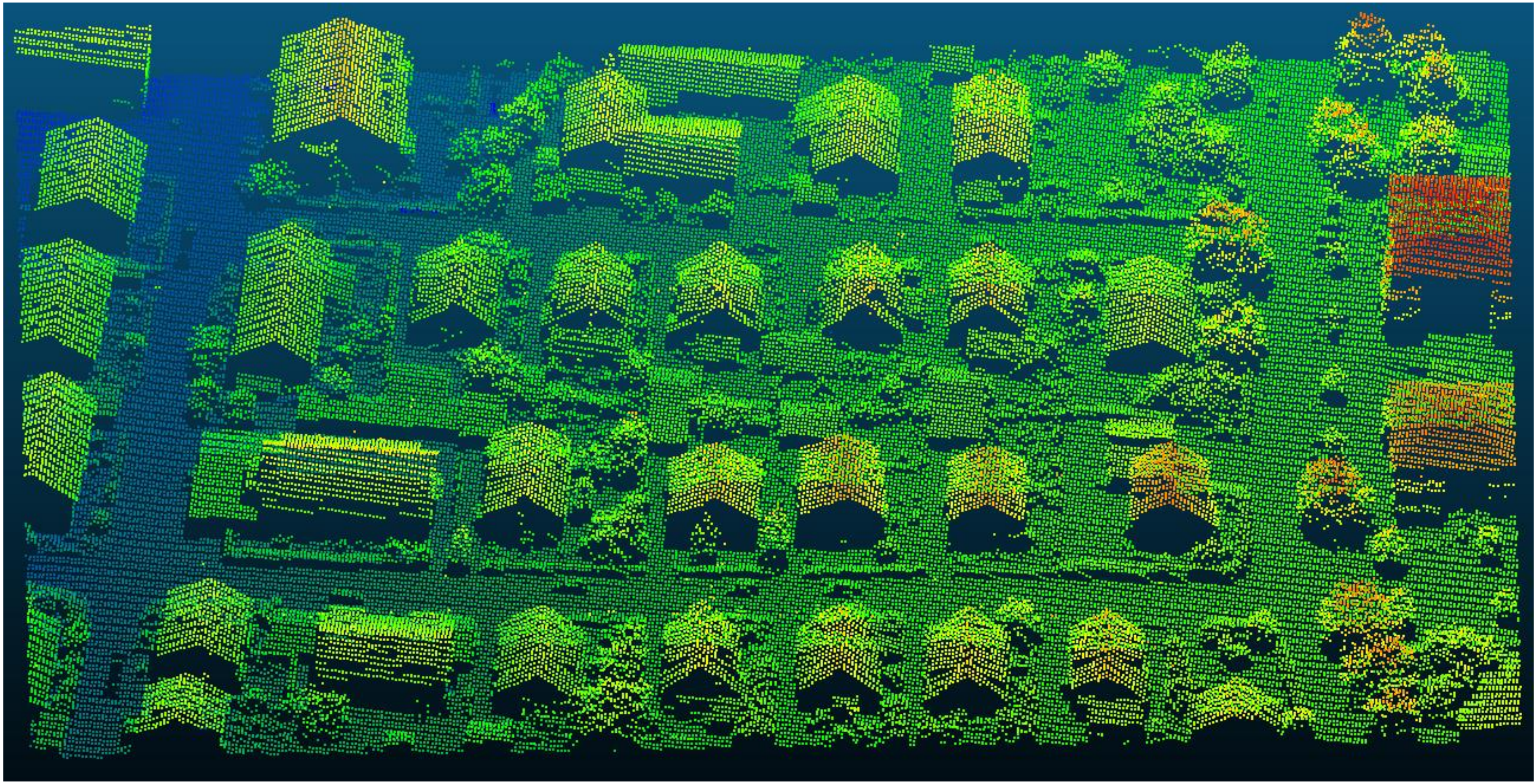
Source: (Haala and Kada, 2010)

3D City Models for Digital Maps



Source: (Haala and Kada, 2010)

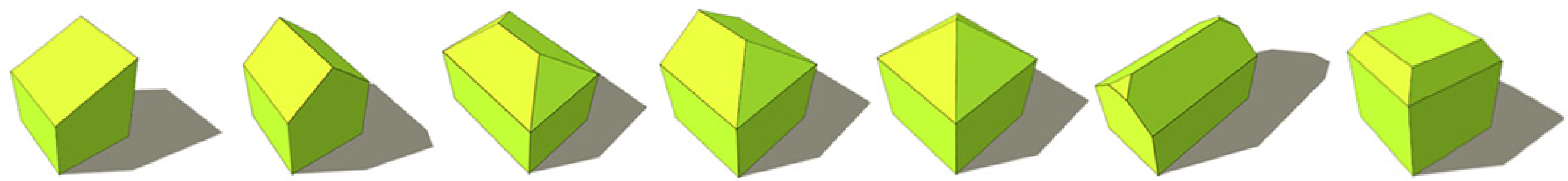
3D Point Cloud from Aerial Laser Scanning



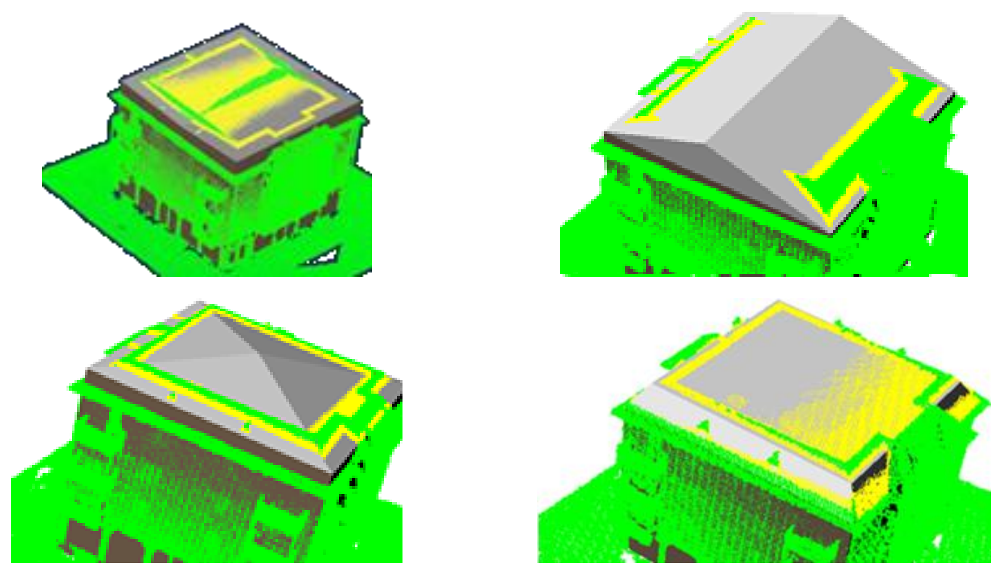
3D Point Cloud from Dense Image Matching

Model-Driven Reconstruction Approaches

- From a library of templates, the most suitable building form is selected and adapted by its parameters to best fit its shape to the input data
  - Templates are (usually) based on rectangular ground plans

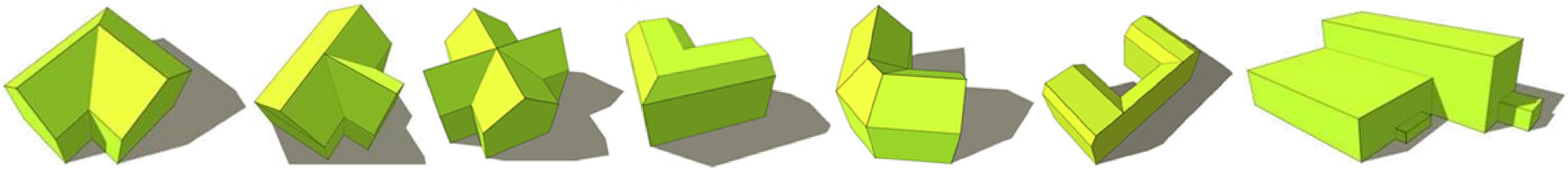


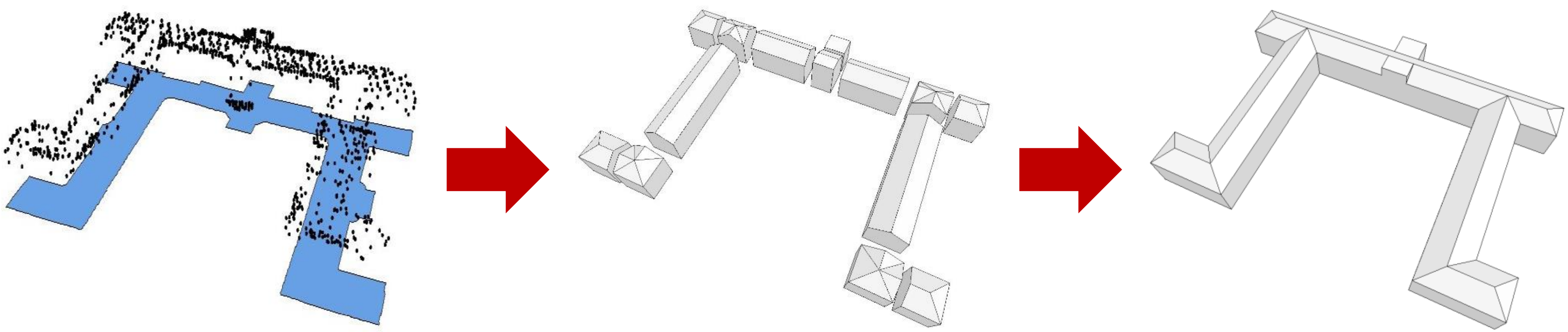
Source: (Nguatem et al., 2013)



Model-Driven Reconstruction Approaches

- Buildings with complex ground plans are assembled from templates with rectangular ground plans (as far as possible)





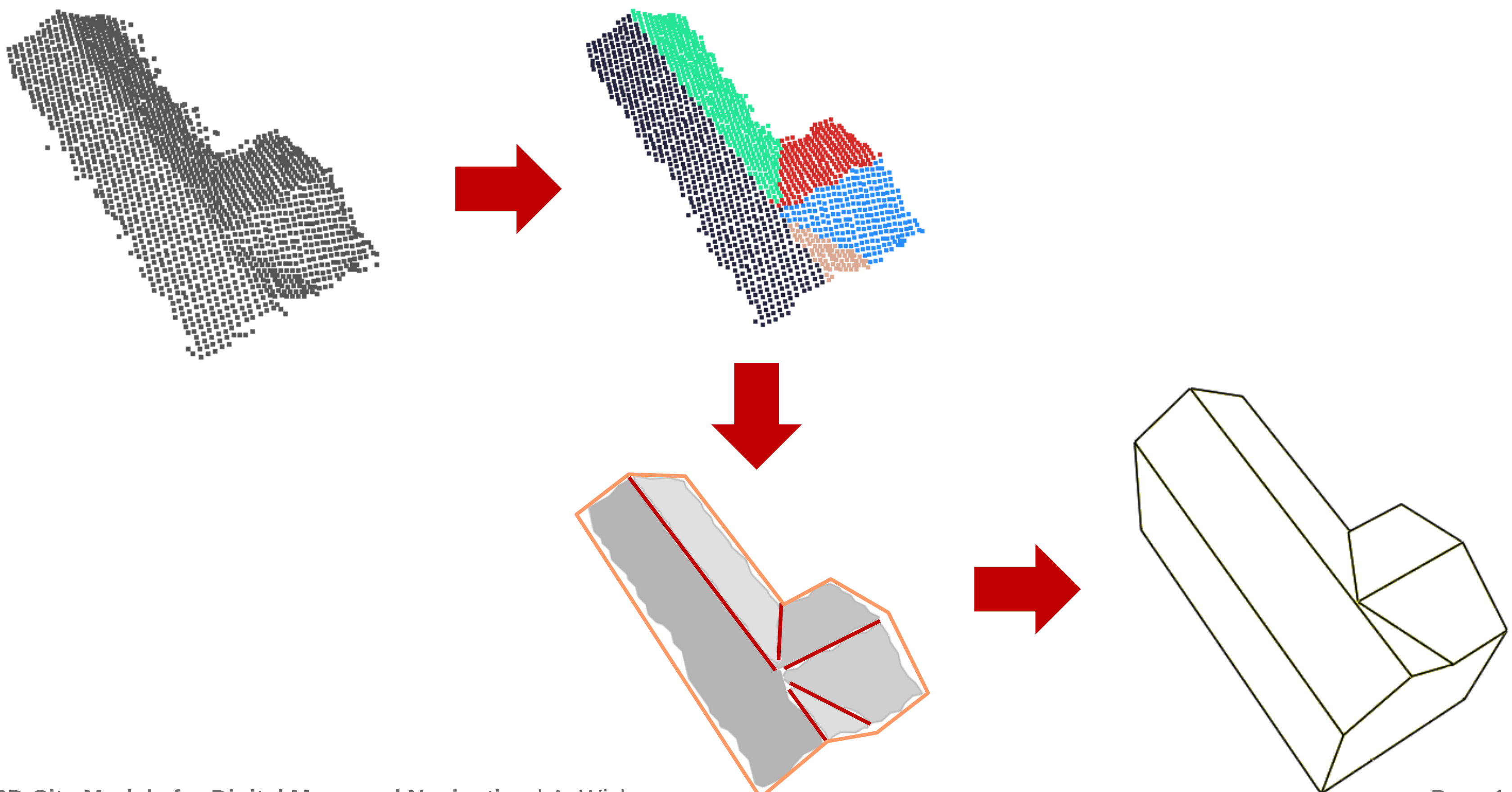
Source: (Kada, 2007)

3D City Model of Berlin

- 80% automation rate
    - → ca. 100,000 buildings were manually post-processed
- < 1s per building
    - → ca. 6 days processing time
- 3,5 billion 3D points
    - → ca. 38 GB data

Data-Driven Reconstruction Approaches

- Input data is gradually enriched with information, aggregated and thus raised to higher levels of information



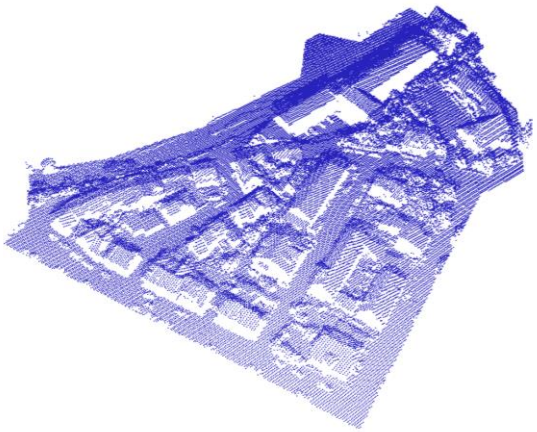
Model-Driven ⇔ Data-Driven

Technische Universität Berlin

	Model-Driven	Data-Driven
Model assumptions	High level (through building templates)	Low level (planar surfaces, horizontal ridge and eaves, symmetries, etc.)
Thresholds	Few thresholds	Many thresholds
Topological correctness	Implicitly by model templates and Boolean operations	Explicit attention is required
Expressive power	Buildings with typical roof shapes and their combination	No restrictions on roof shapes
Input data	Low point density, high noise, strong smoothing (incl. satellite and radar data)	High point density with high accuracy

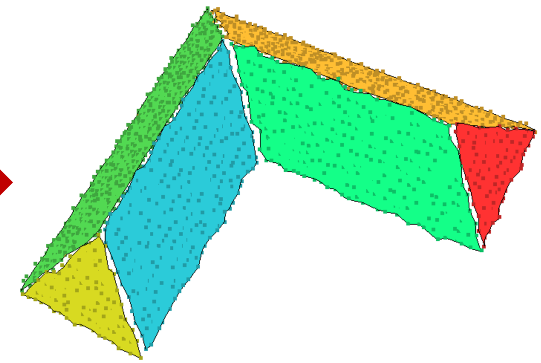
Grammar-Guided Reconstruction Approach

Technische Universität Berlin

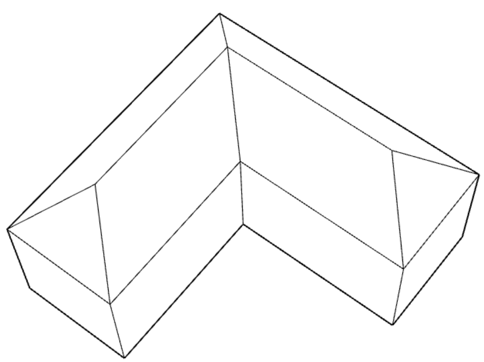


Point Cloud (ALS)

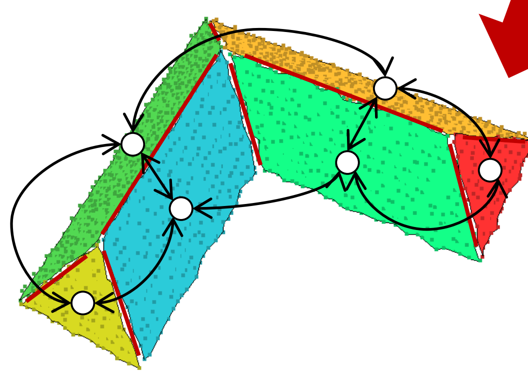
Building Point Extraction



Segmentation

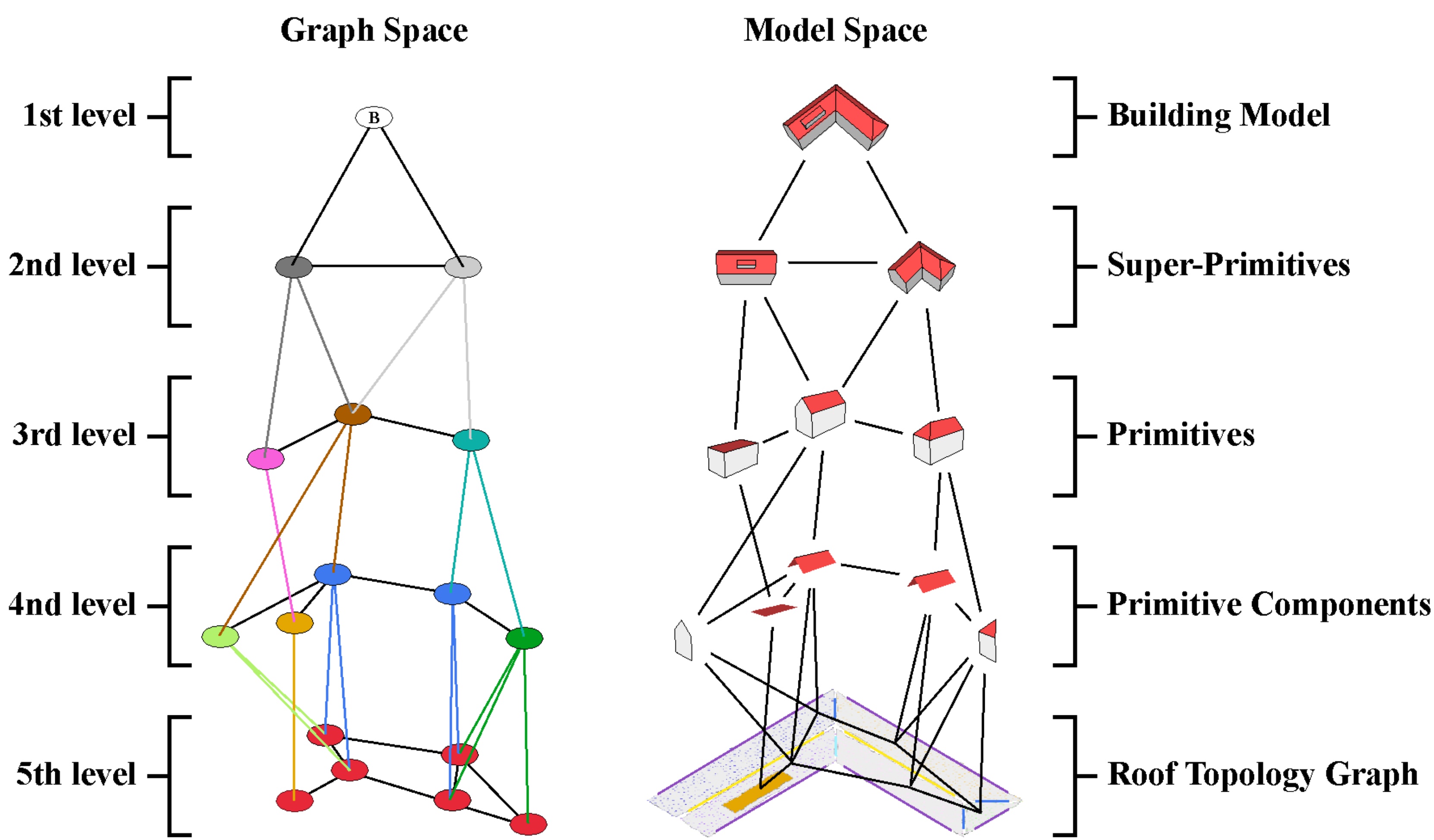


3D Building Model Construction



Shape Recognition

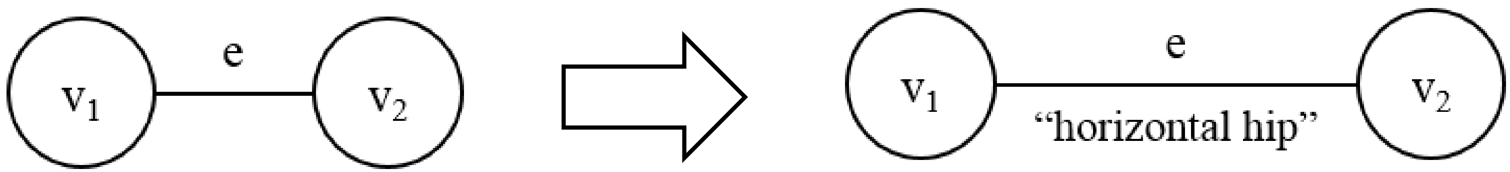
Multi-Scale Knowledge Graph



Graph Grammar

- Replace in the multi-scale knowledge graph

the left-hand side of the production rule with its right-hand side



provided that the precondition

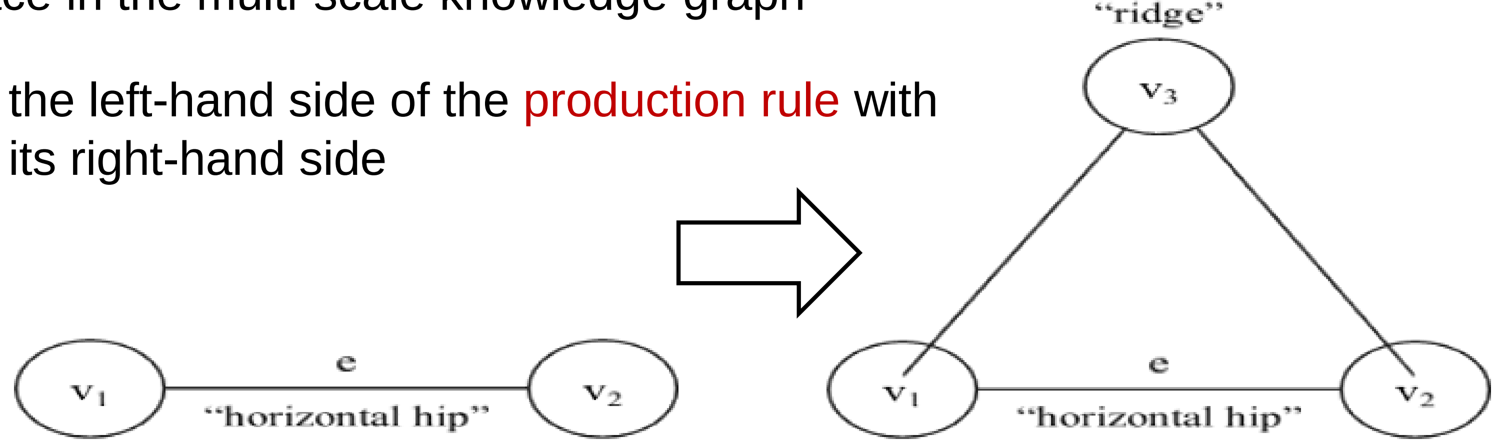
$$
\begin{aligned}
&O_z(v_1) = \text{"sloped"} \wedge O_z(v_2) = \text{"sloped"} \wedge AD(e) = \text{"3D"} \wedge \\
&Presence(e) = \text{"Surface Points"} \wedge O_{intersection}(e) = \text{"horizontal"} \wedge \\
&Visibility(e) = \text{"}-\text{"} \wedge CP\_PC(e) = \text{"none"} \wedge \\
&\left(O_{xy}(e) = \text{"}\leftrightarrows\text{"} \vee O_{xy}(e) = \text{"}\rightrightarrows\text{"}\right) \wedge CV(e) > threshold
\end{aligned}
$$

is met

Graph Grammar

- Replace in the multi-scale knowledge graph

  the left-hand side of the production rule with its right-hand side



provided that the precondition

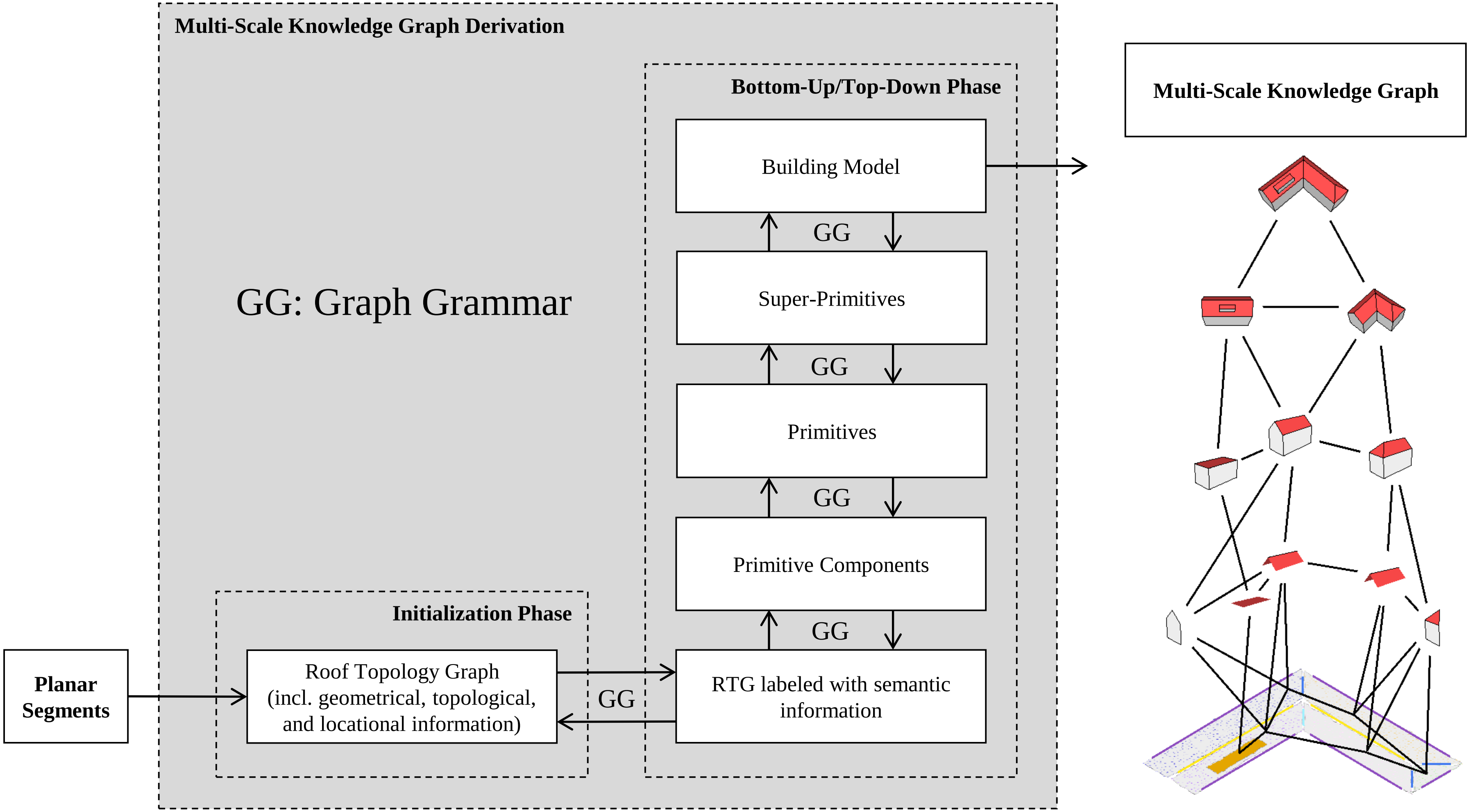
$$O_z(v_1) = \text{"sloped"} \wedge O_z(v_2) = \text{"sloped"} \wedge O_{xy}(e) = \text{"} \leftrightarrows \text{"} \wedge CV(e) > threshold$$

and the postcondition

$$OL\big(e, intersection(v_1.plane, v_2.plane)\big) > threshold$$

are met

Grammar-Guided Shape Recognition



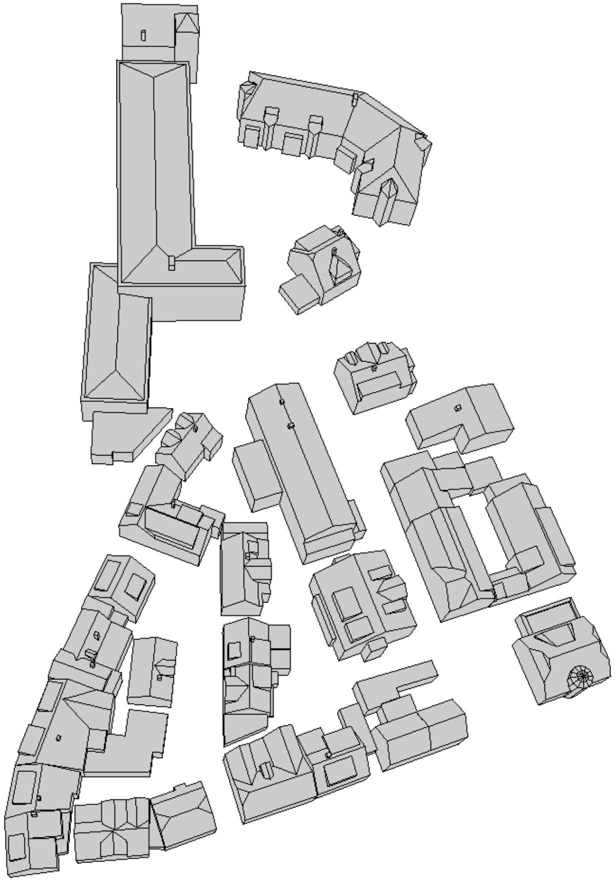
Grammar-Guided Shape Recognition

- Sub-graph matching is NP-complete and thus not efficient
    - → Application of all productions would cause much processing time
- (Neighboring) Buildings often comprise repetitive structures

Source: http://www.christoph-gauben.de/

- Probabilities are assigned to the production rules
- Reinforcement learning changes the probabilities of the production rules

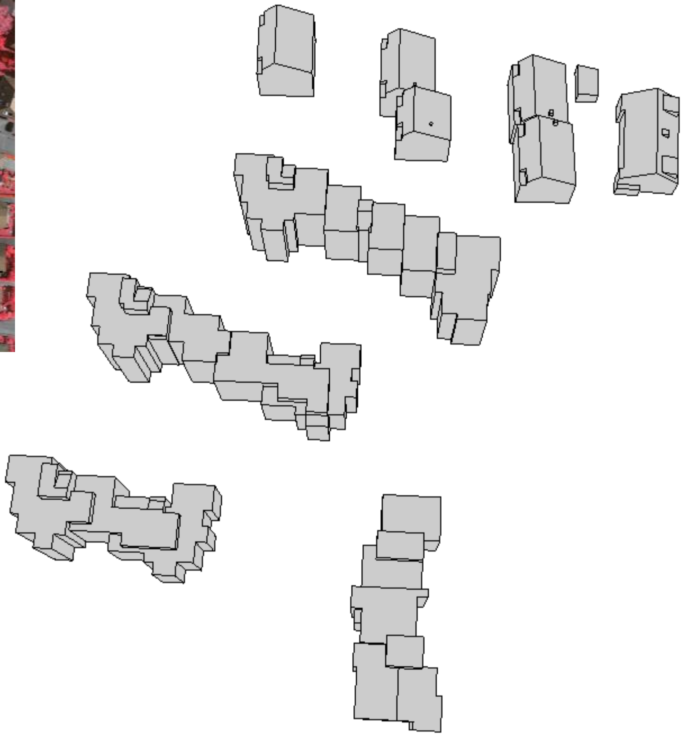
ISPRS Benchmark: Vaihingen (AOI 1)



	Comp [%]	Corr [%]
CKU	86.8	98.9
ITCE1	60.8	96.6
ITCE2	65.3	**100.0**
ITCX1	76.0	99.2
ITCX2	84.7	96.2
ITCX3	**89.2**	96.4
TUD	67.4	96.2
VSK	72.2	96.7
YOR	88.2	98.5
MON	76.4	83.3
MON_mod	75.0	95.3
MON2	66.0	91.7
TUD2	73.3	**100.0**
MEL_HE	88.2	99.5
BNU2	84.7	99.3
MON5	74.3	98.7
TUB	**89.2**	95.9

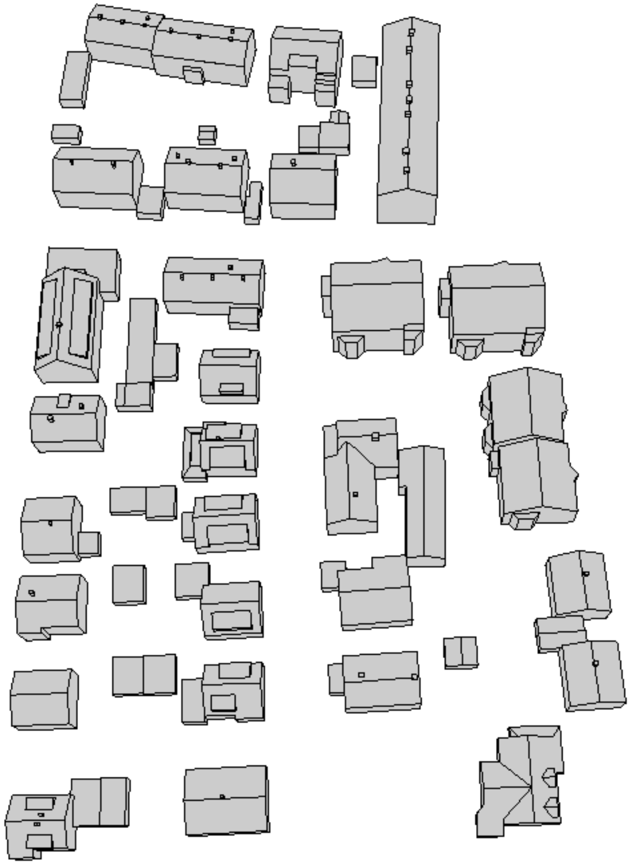
ISPRS Benchmark: Vaihingen (AOI 2)

Technische Universität Berlin



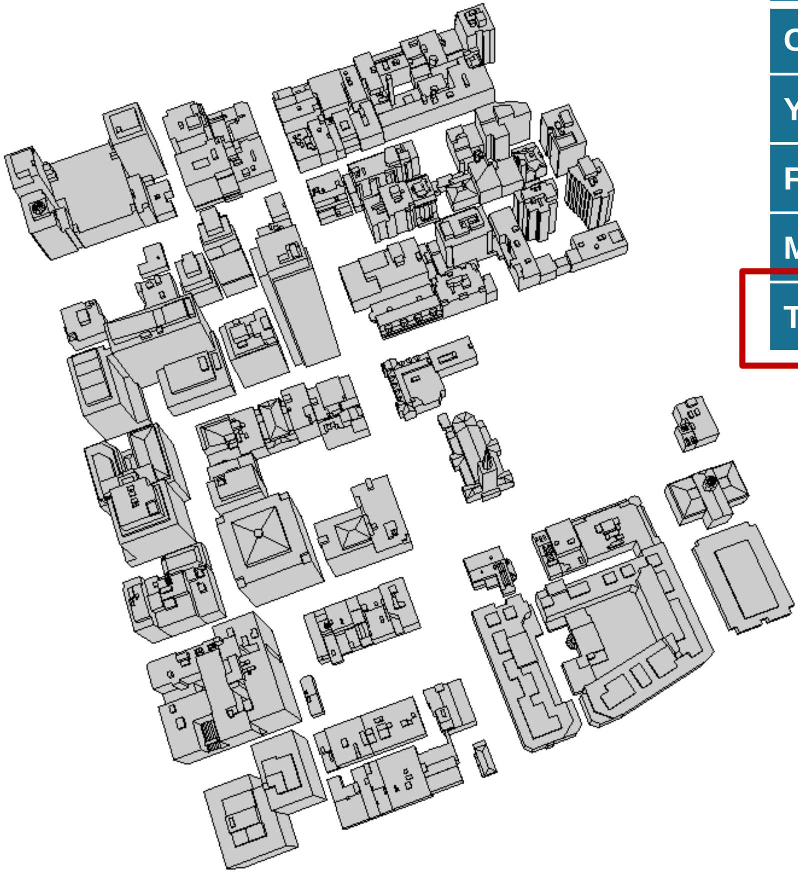
	Comp [%]	Corr [%]
CKU	78.3	93.1
ITCE1	**79.7**	73.7
ITCE2	**79.7**	95.0
ITCX1	62.3	95.1
ITCX2	75.4	98.2
ITCX3	71.0	**100.0**
TUD	68.1	98.1
VSK	73.9	**100.0**
YOR	66.7	**100.0**
CAS	63.8	**100.0**
MON	73.9	91.9
MON_mod	69.6	96.8
MON2	71.0	90.7
TUD2	71.0	**100.0**
MEL_HE	71.0	98.1
BNU2	73.9	**100.0**
MON5	72.5	94.8
TUB	72.5	97.1

ISPRS Benchmark: Vaihingen (AOI 3)



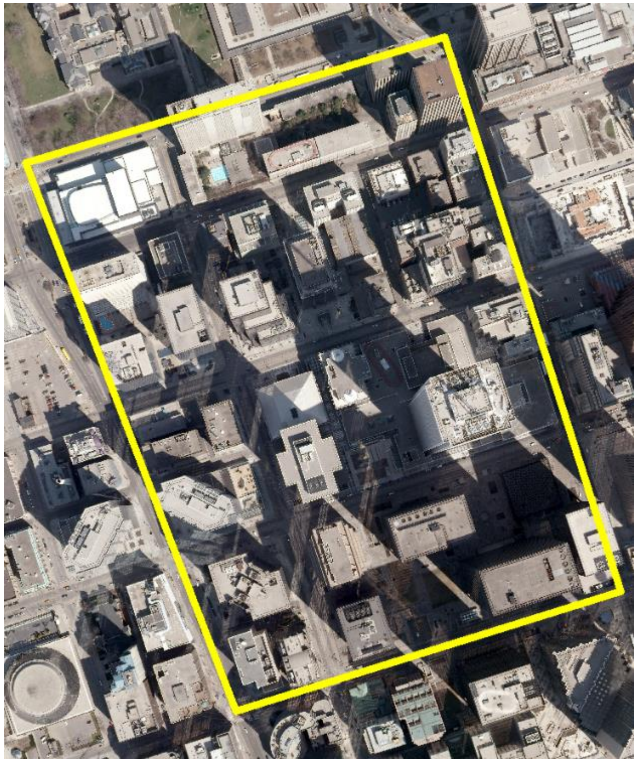
	Comp [%]	Corr [%]
CKU	81.3	98.4
FIE	82.6	83.1
ITCE1	67.7	**100.0**
ITCE2	64.3	**100.0**
ITCX1	70.2	**100.0**
ITCX2	86.0	84.4
ITCX3	**88.1**	88.2
TUD	74.5	93.0
VSK	76.6	99.1
YOR	84.7	**100.0**
CAS	73.2	**100.0**
MON	82.1	93.9
KNTU	80.4	96.7
BNU	87.2	**100.0**
MON_mod	74.5	96.2
MON2	73.2	89.2
TUD2	73.6	**100.0**
MEL_HE	82.6	97.8
WROC	80.4	98.2
WROC_2a	81.3	**100.0**
WROC_2b	81.7	**100.0**
MON5	80.9	99.3
TUB	85.1	96.7

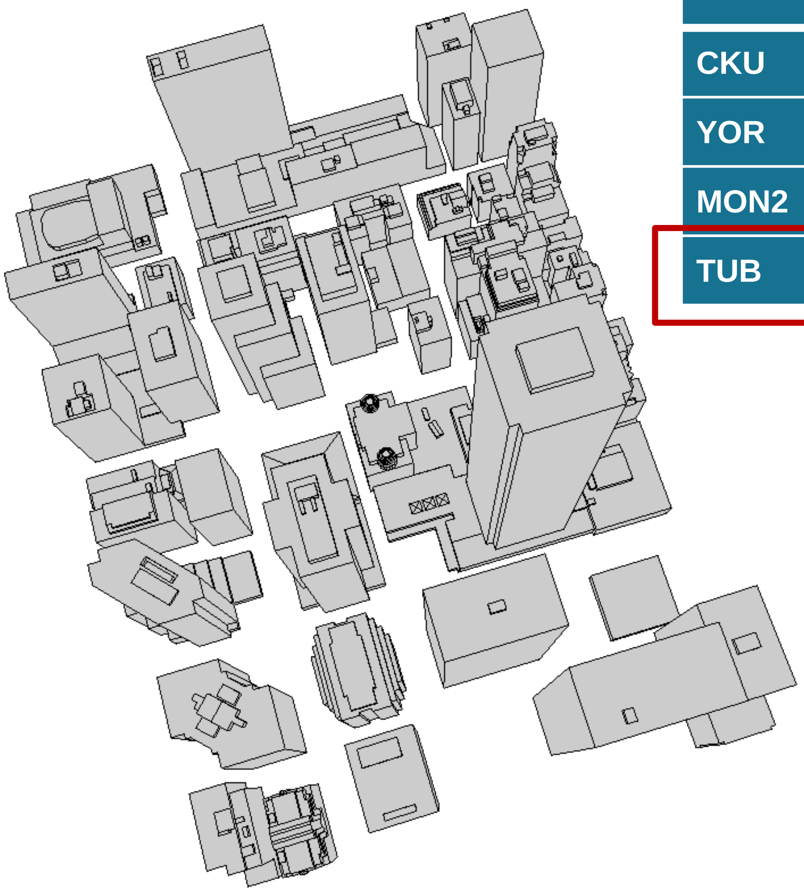
ISPRS Benchmark: Toronto (AOI 4)



	Comp [%]	Corr [%]
CKU	68.6	80.2
YOR	75.5	**97.5**
FIE	52.3	91.5
MON2	70.2	78.3
TUB	**88.1**	93.4

ISPRS Benchmark: Toronto (AOI 5)





	Comp [%]	Corr [%]
CKU	70.3	83.3
YOR	64.5	**85.8**
MON2	67.9	80.7
TUB	**84.7**	82.2

ISPRS Benchmark Result

Evaluation result on a per-roof plane level
(threshold for classification as a true positive is 50%).

Data set	Area	Completeness balanced by area [%]	Correctness balanced by area [%]	Quality balanced by area [%]
Vaihingen	1	94.2	99.0	93.4
	2	94.9	99.7	94.7
	3	95.9	99.6	95.6
	Sub-total	95.0	99.4	94.6
Toronto	4	98.2	95.3	93.7
	5	99.4	91.5	90.9
	Sub-total	98.8	93.4	92.3
Total		96.5	97.0	93.7

Thank you

for your attention!

Wichmann, A., 2017. Grammar-Guided Reconstruction of Semantic 3D Building Models From Airborne LiDAR Data Using Half-Space Modeling. Dissertation (eingereicht am 21.08.2017), Technische Universität Berlin