Data-Driven Modeling in Computer Graphics

ISTD 50.017

Graphics & Visualization

Sai-Kit Yeung

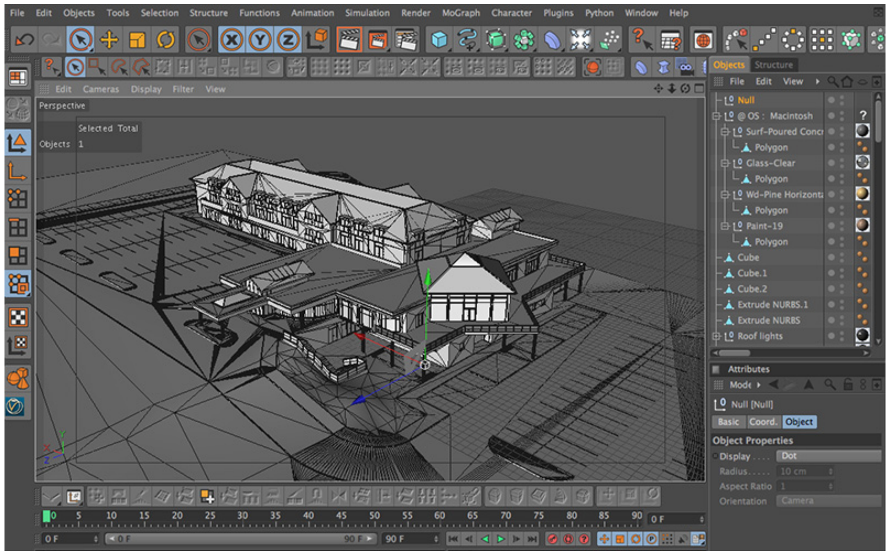
Introduction

Data-driven approaches can be devised to:

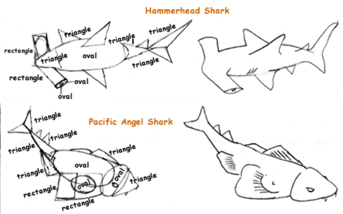
- generate realistic 3D models automatically
- facilitate modeling tasks by human users

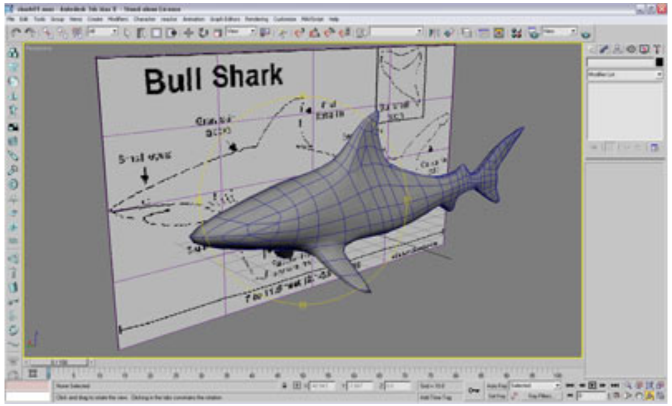
The Modeling Problem in Computer Graphics.

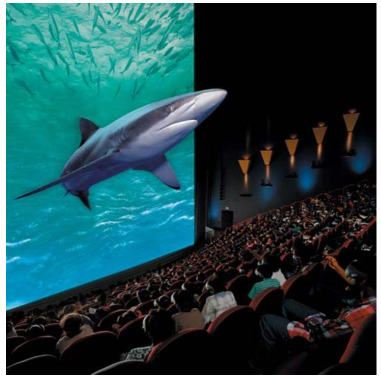
Process of creating models to represent 3D objects in the virtual environment



Role in Computer Graphics



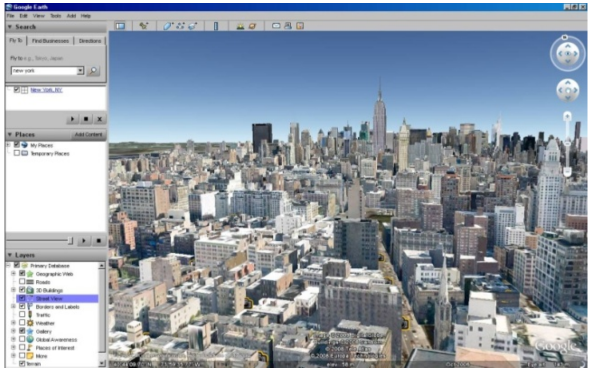




Design Idea → Modeling → Shading & Texturing → Lighting → Animation → Rendering → Display

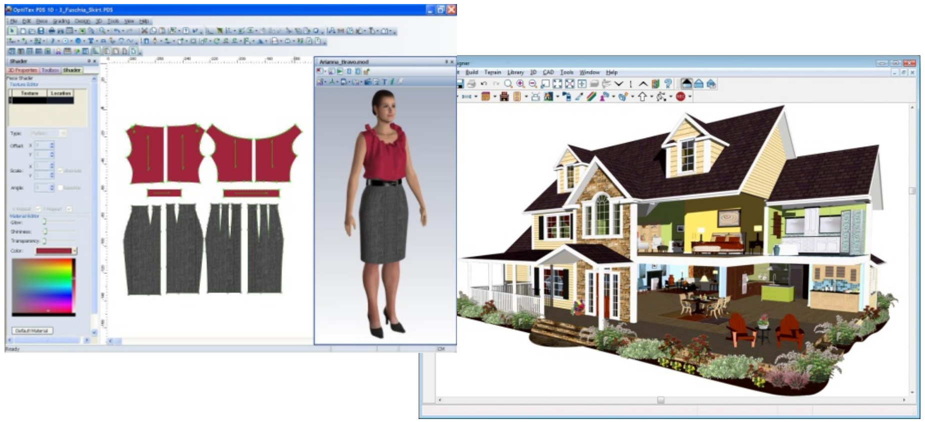
Need for 3D Models

Visualization:



Entertainment:

CAD:



3D Printing:

Model Complexity

Virtual Environment:

Battlezone, 1980

StarFox, 1993

Super Mario 64, 1997

GTA5, 2013

Virtual Character:

Final Fantasy VII, 1997

Final Fantasy VIII, 1999

Final Fantasy XI, 2002

Final Fantasy XV, upcoming

Outline

Introduction

Motivation

Research showcases

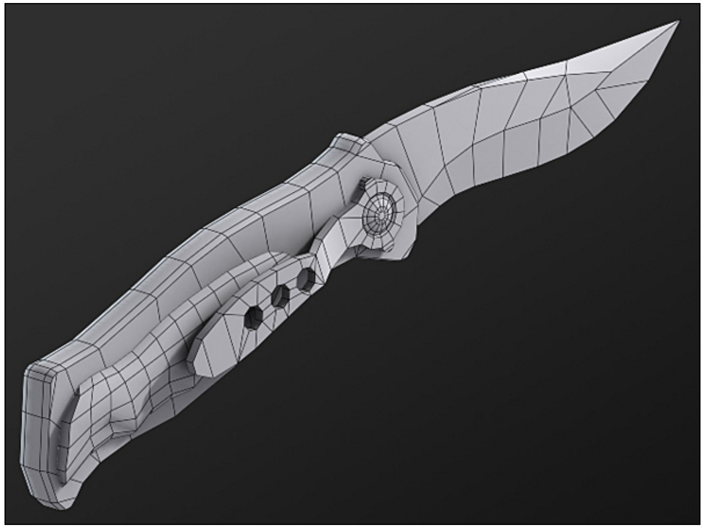
Conclusion

Common Approaches

1) Manual Creation, e.g.,

- Polygonal Modeling: man-made objects
- Digital Sculpting: organic objects

Polygonal Modeling



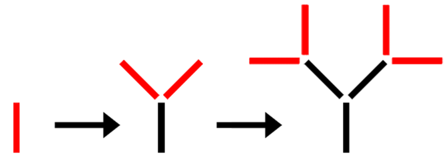
Digital Sculpting [ZBrush]

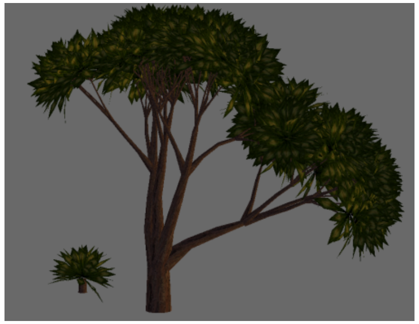
Common Approaches

2) Automatic Synthesis, e.g.,

- Rule-based / grammar

Procedural trees:

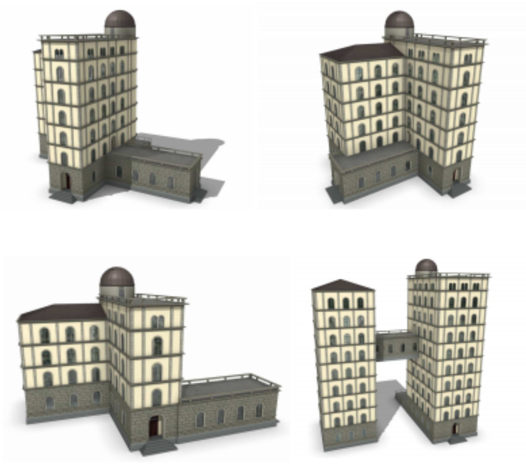




Procedural Streets / Buildings:

[Chen et al. 2008]

[Muller et al. 2006]



Limitation

1) Labor intensive & tedious
2) Huge money & time investment
3) Non-scalable
4) Limited productivity & creativity

Virtual San Francisco, Google Earth

Bottleneck is Modeling?

	Super Mario Bros	Super Mario 64	GTA5
			
Scene	2D Mario world	3D Mario world	3D models of whole LA county
Release date	1985	1997	2013
Time needed	<1 year	~2 years	~4 years
Team size	<5 people 	~15 people 	>1000 people Budget: >$100 million  …

Need for Modeling Research

We want:

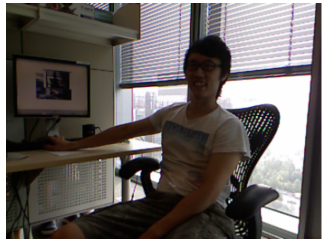
1) more 3D models in shorter time
2) more intuitive tools
3) more accurate models (scientific visualization)
4) creativity support for all (laymen & artists)

Data-driven Modeling

1) Easy Access to Data

- "Data age", take advantage of big, shared data
- Collaborative design space

RGB Image:



Depth camera:

2) Easy Acquisition of Data

- Low-cost acquisition devices
- RGB-D cameras, 3D scanner

Point cloud from RGB-D:

3) Rich Knowledge in Data

- Bottom-up can be easier (e.g. vision)
- Difficult to create otherwise

Potentials

1) Automatic model synthesis
2) Facilitate interactive modeling
3) Flexible & powerful considerations
   - Formulated as cost terms
   - Difficult to express by rules otherwise
   - Possible to control relative importance
4) Explore design possibilities
   - Multiple optimal solutions possible

Challenges

1) What data?
2) How to acquire data?
3) What features to use from data?
4) How to represent data?
5) How to optimize w.r.t. data?

Specific to the modeling task on hand

Data source:

Modeling tools (to be devised):

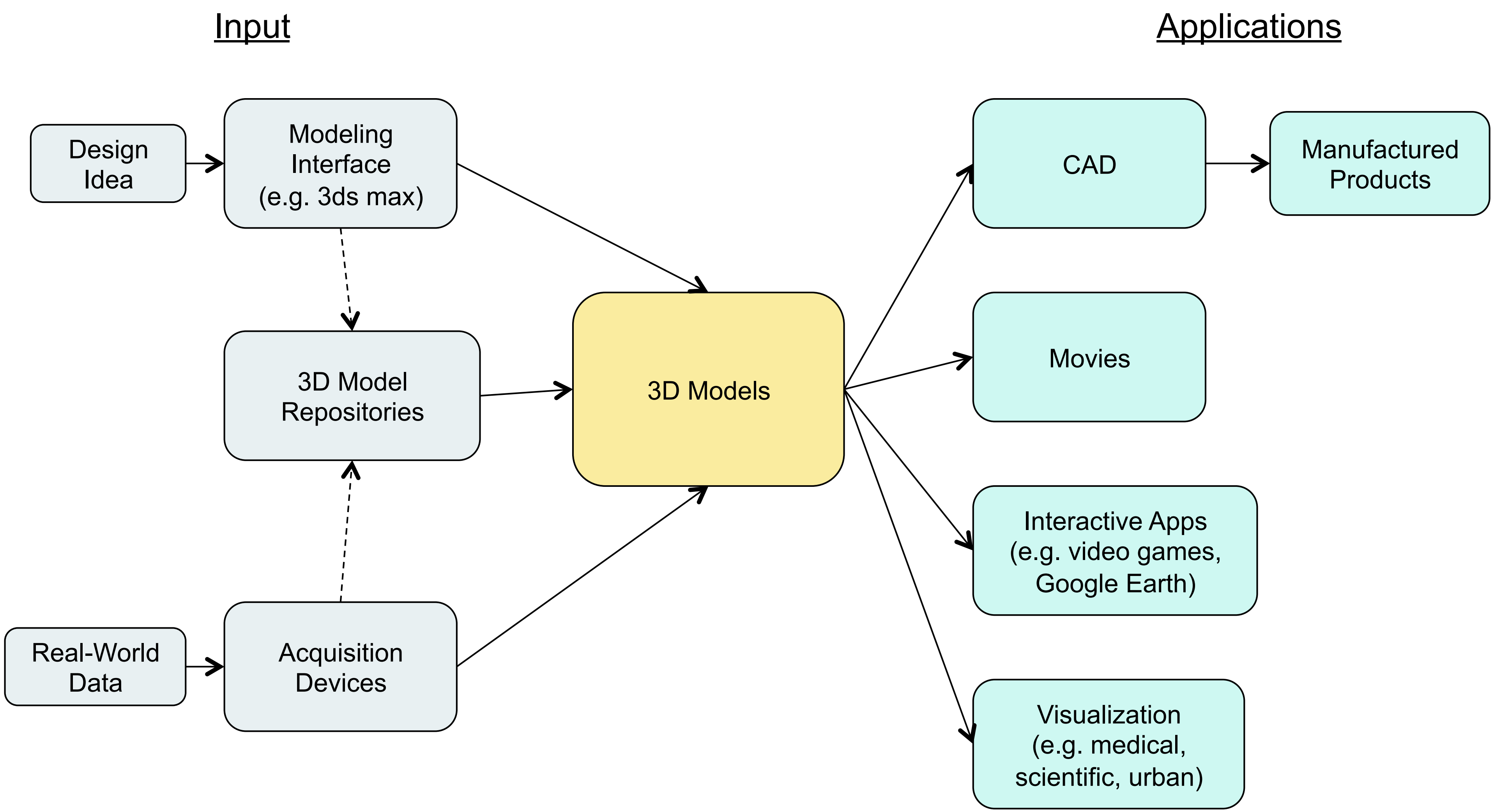
Models created:

Data-driven Modeling

General Steps:

1) Identify useful features from data
2) Represent useful features in a statistical model
3) Optimize w.r.t. statistical model and other criteria
4) Optimization result → Modeling result

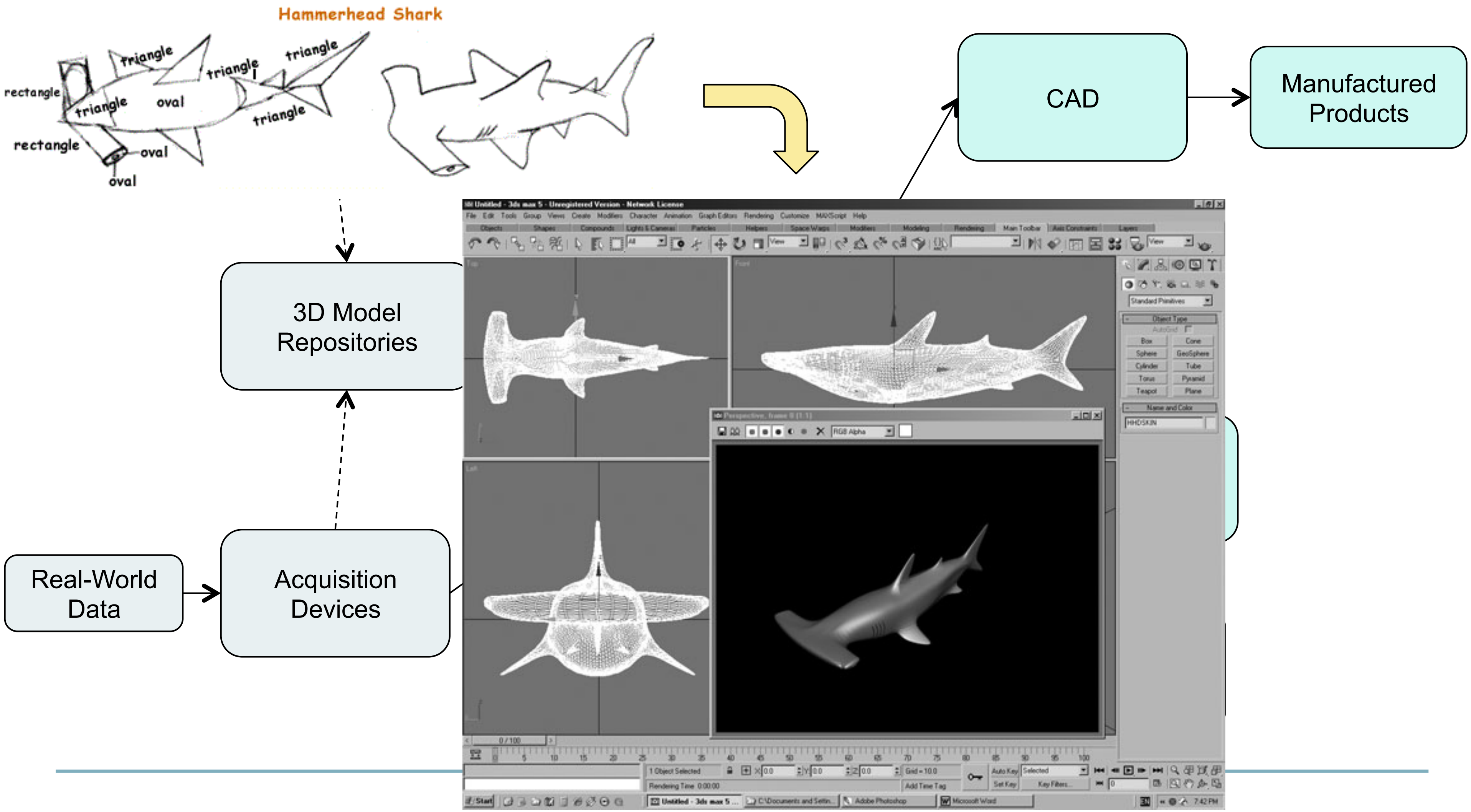
The Big Picture



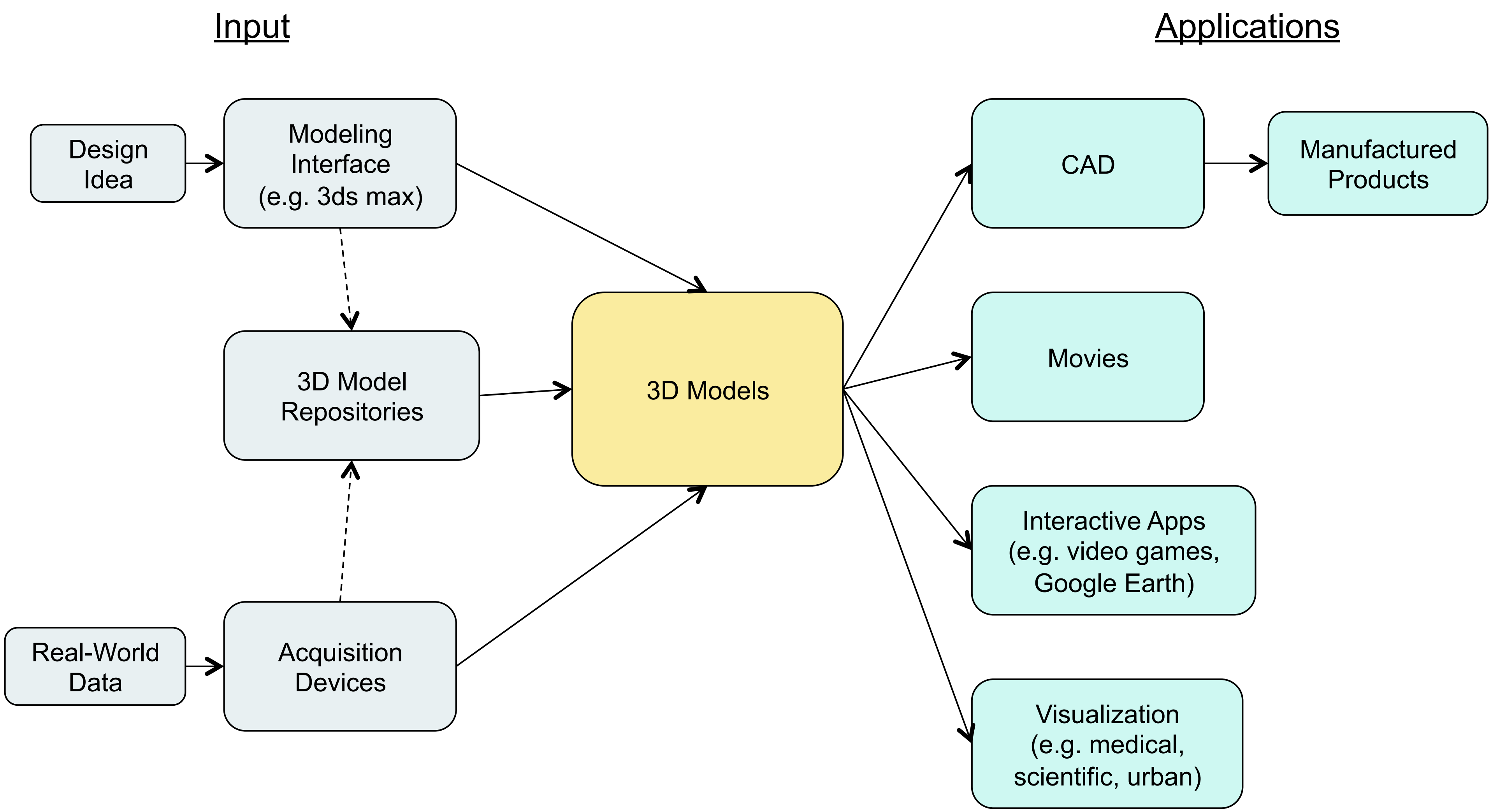
The Big Picture: Graphics-Perspective

Input

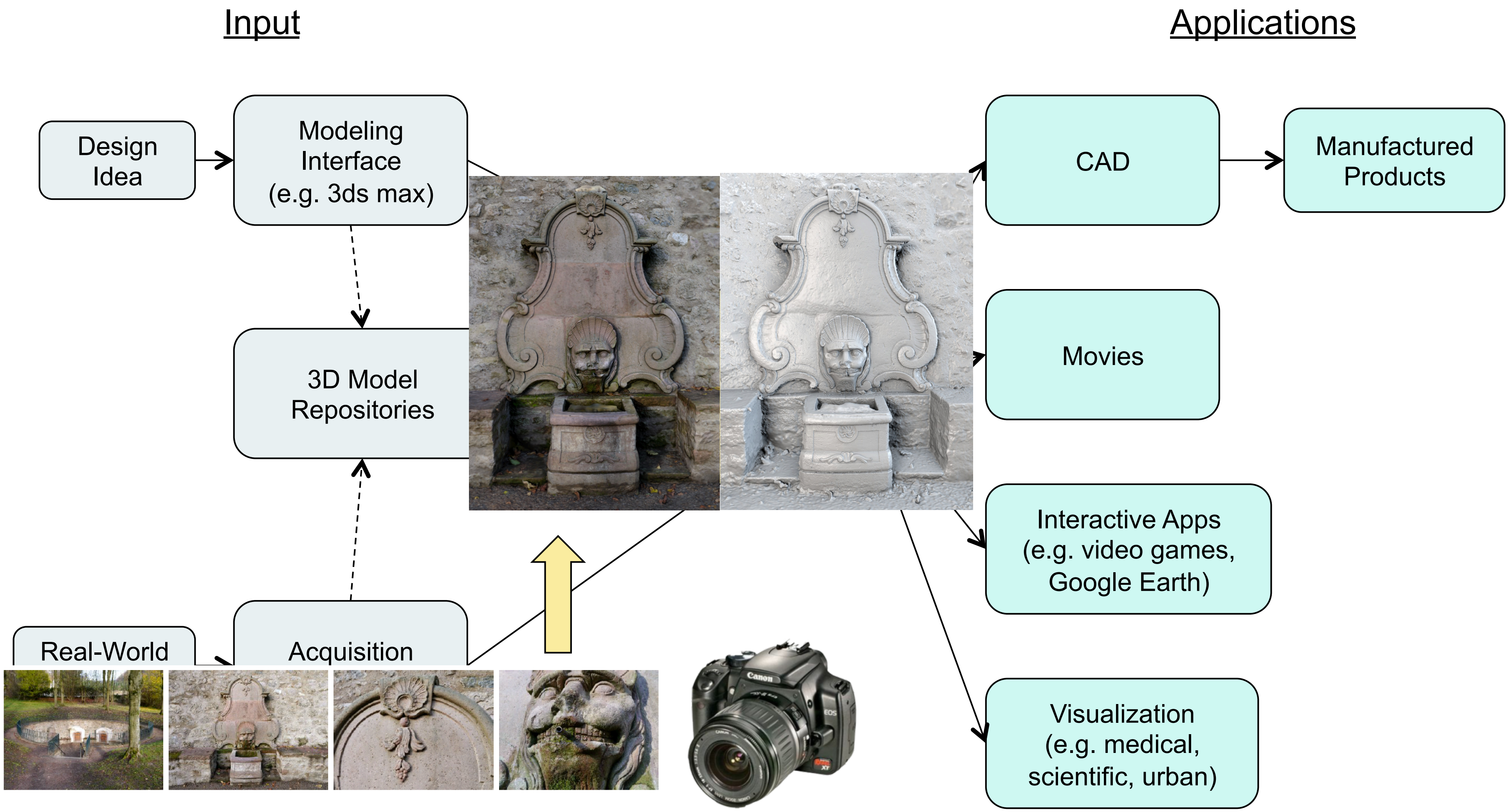
Applications



The Big Picture

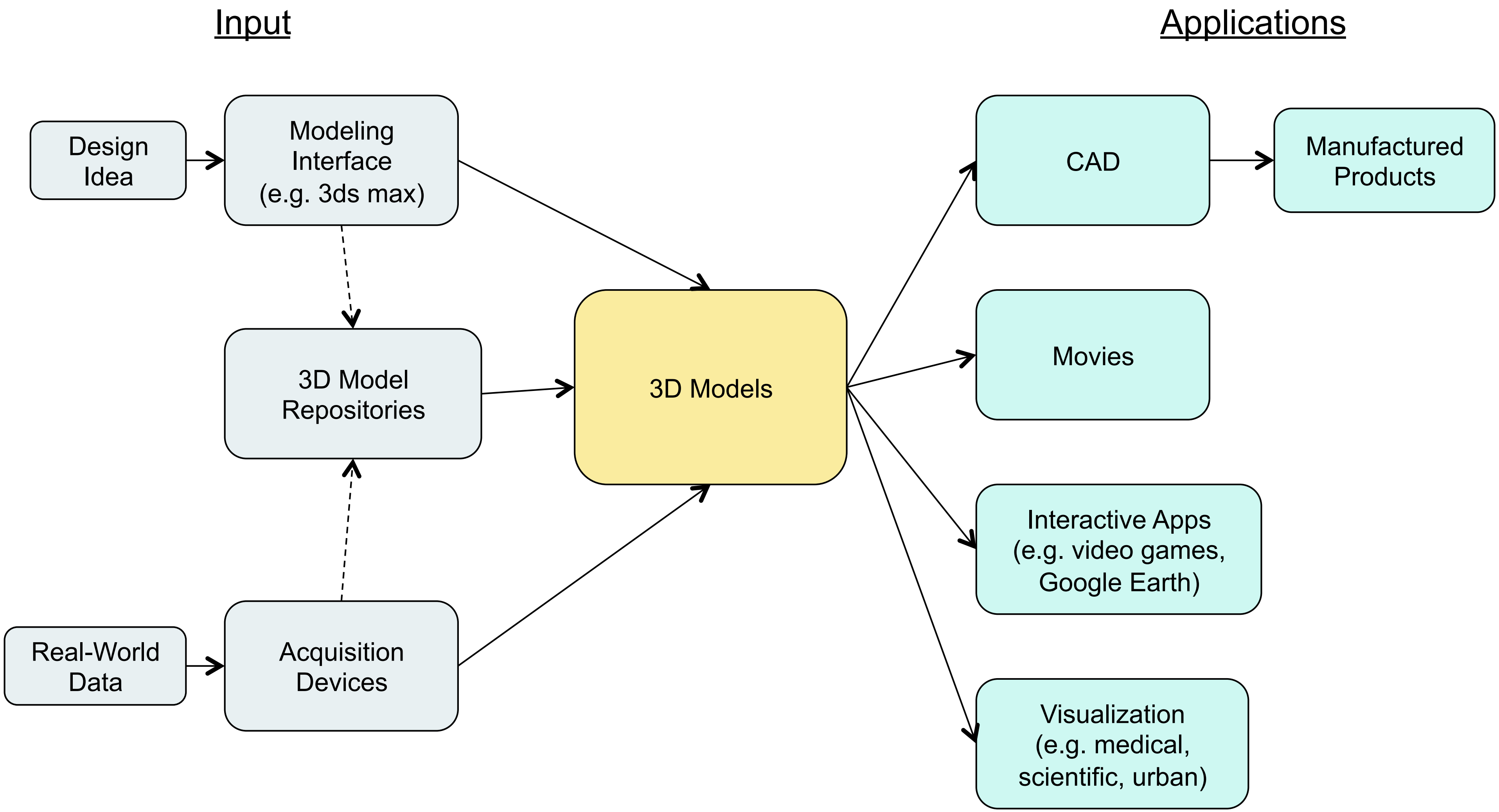


The Big Picture: Vision-Perspective



[Fuhrmann and Goesele 2014]

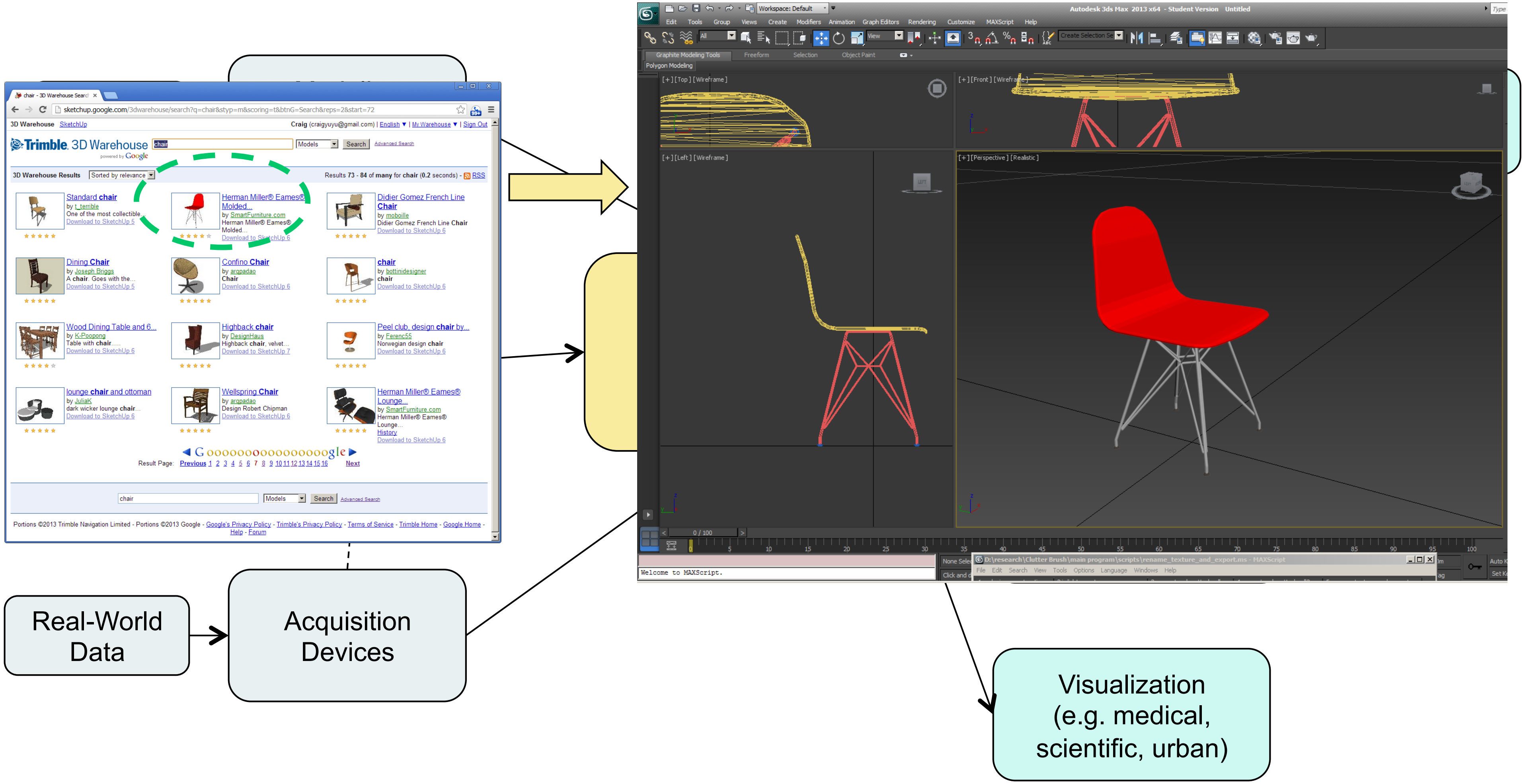
The Big Picture



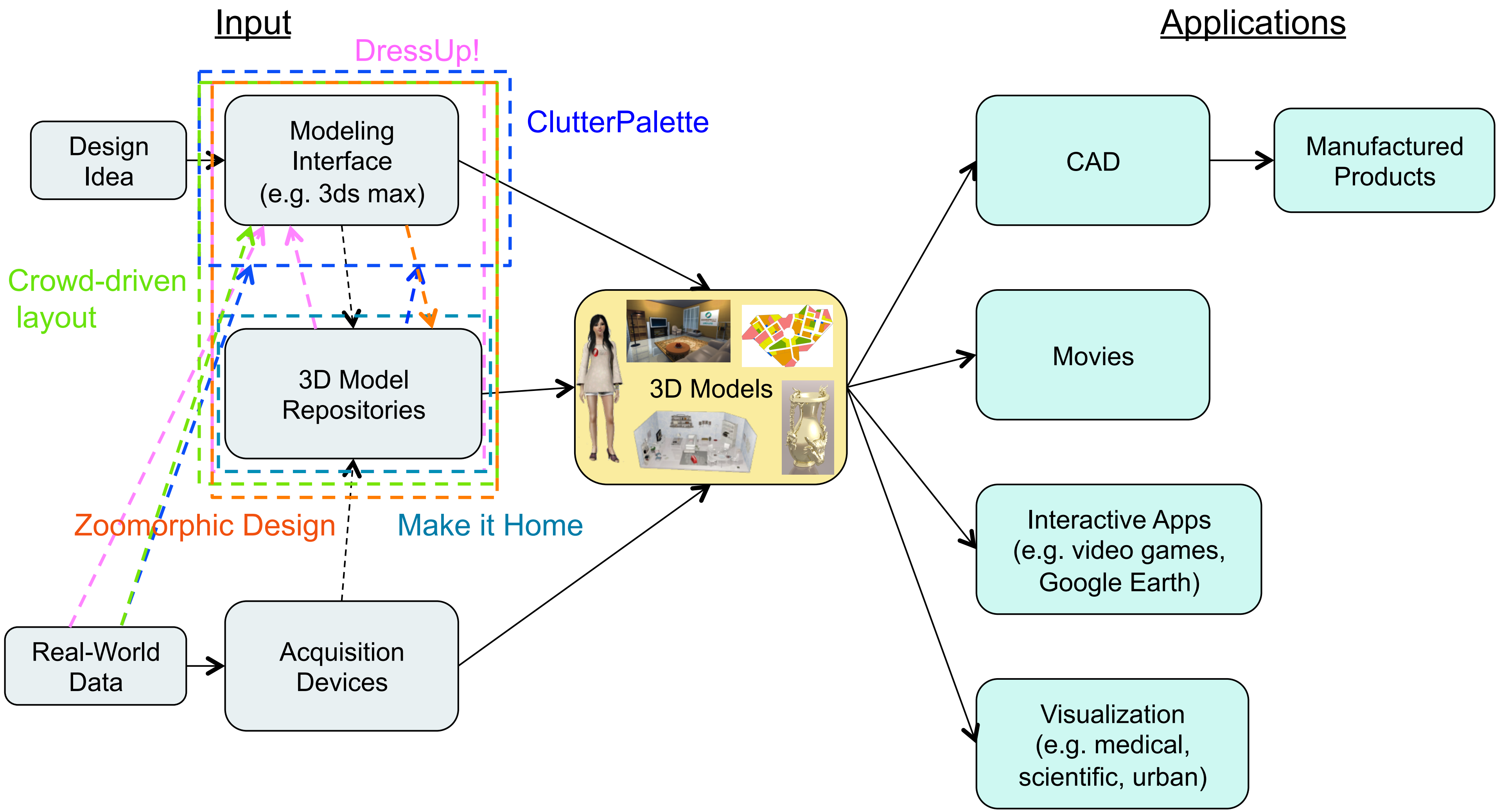
The Big Picture: 3D Model Repositories

Input

Applications



The Big Picture: Related Research



Outline

Introduction

Motivation

Research showcases

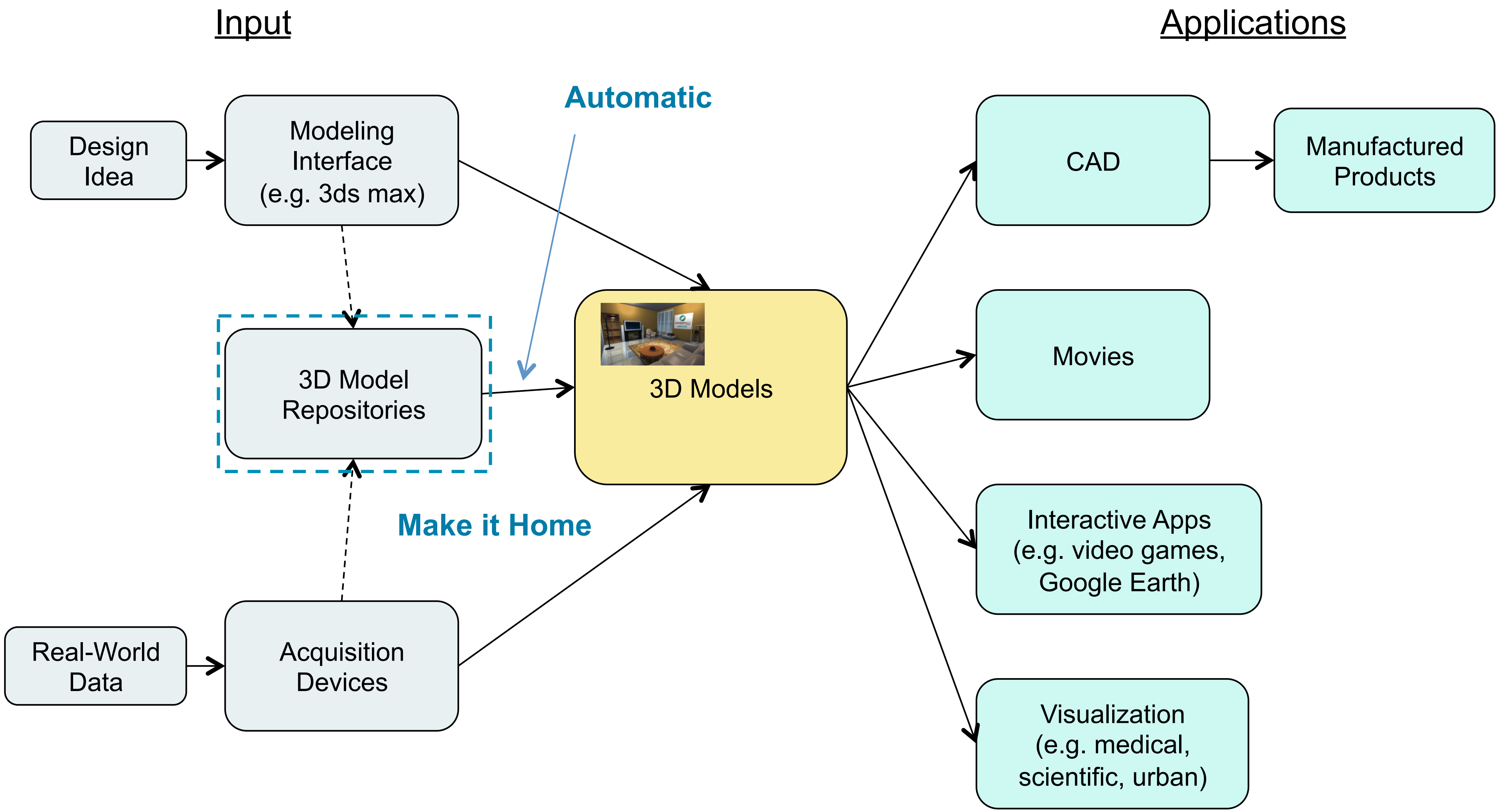
- **Scene Modeling**
- Character Modeling
- Shape Modeling

Conclusion

Scene Modeling

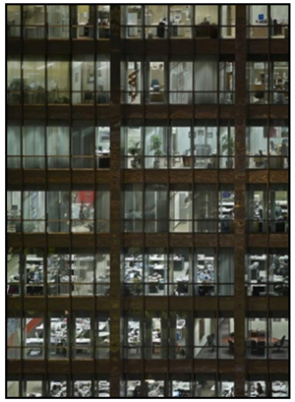
"Make it Home: Automatic Optimization of Furniture Arrangement", *SIGGRAPH 2011*
Lap-Fai Yu, Sai-Kit Yeung, Chi-Keung Tang, Demetri Terzopoulos, Tony F. Chan, Stanley J. Osher

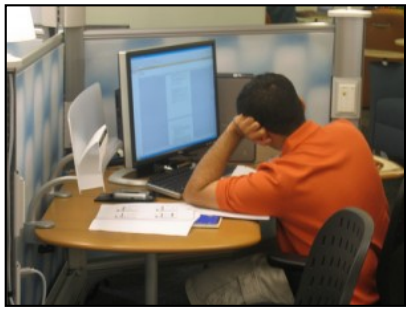
The Big Picture: Make it Home



Motivation

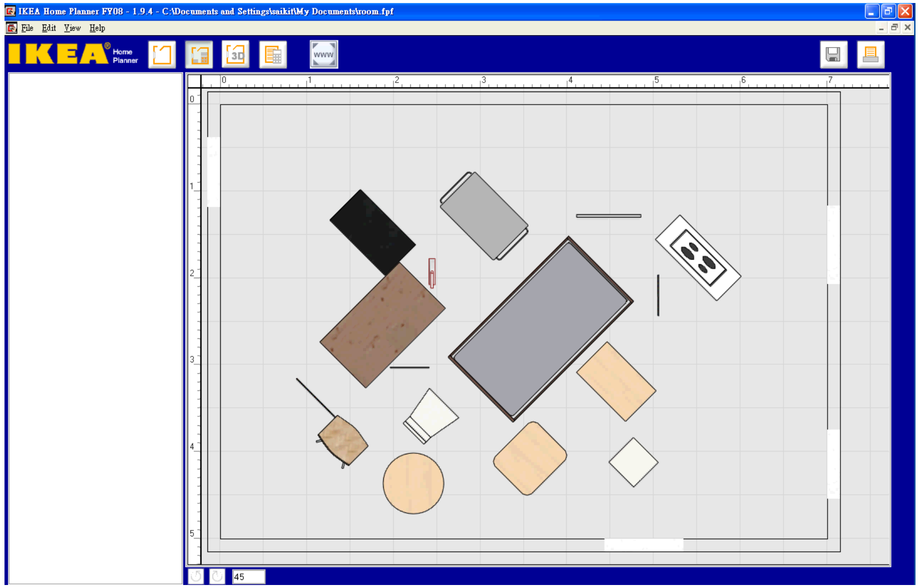
1) Large-scale virtual worlds
2) Interior design
   - Manual process
   - Labor-intensive
   - Time-consuming





Motivation

Traditional (Manual):



Our Method (Automatic):

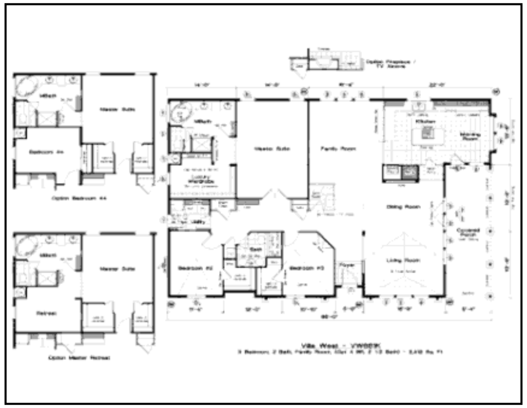
Related Work

City Synthesis

- Procedural Modeling of Cities (SIGGRAPH 2001)
- Procedural Modeling of Buildings (SIGGRAPH 2006)
- Interactive Procedural Street Modeling (SIGGRAPH 2008)

Floor Plan

- Computer-generated residential building layouts (SIGGRAPH ASIA 2010)



Related Work

Furniture Arrangement

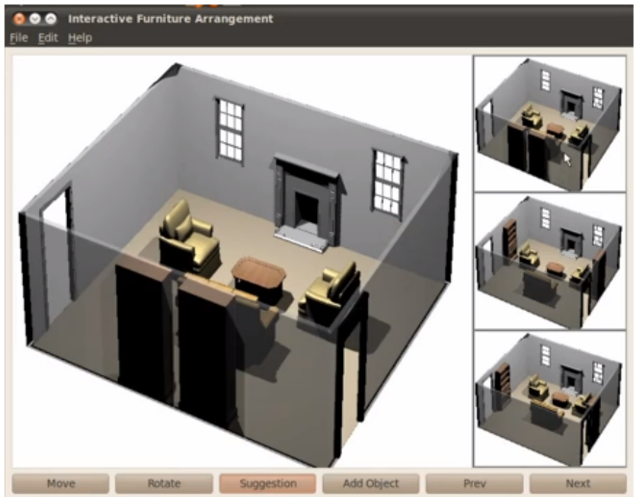
- Procedural Arrangement of Furniture for real-time Walkthroughs (Computer Graphics Forum 2009)
- Major Problems:
  - Manual specification per object
  - Non-scalable
  - No ergonomics (e.g. visibility, accessibility, pathway)
  - “Unlivable”

No ergonomics consideration

Related Work

Recent Work

- Interactive Furniture Layout using Interior Design Guidelines (SIGGRAPH 2011)
- Synthesizing open worlds with constraints using locally annealed reversible jump MCMC (SIGGRAPH 2013)



[Merrell et al. 2011]

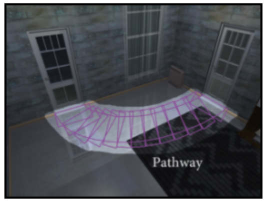
[Yeh et al. 2011]

Overview

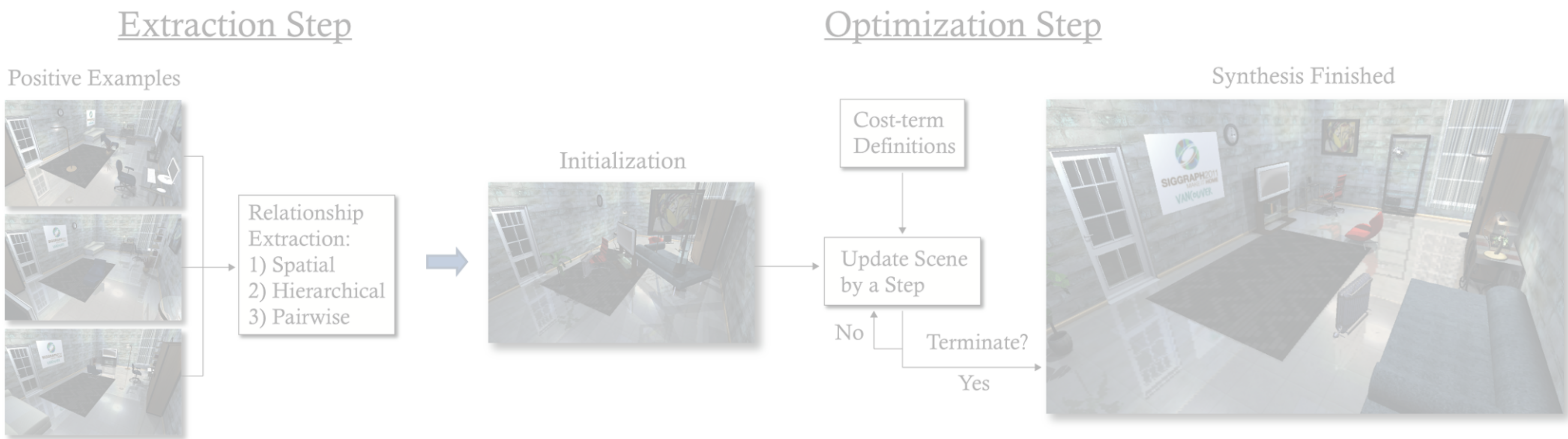
Input
- Room + Furniture

Output
- Furnished Room

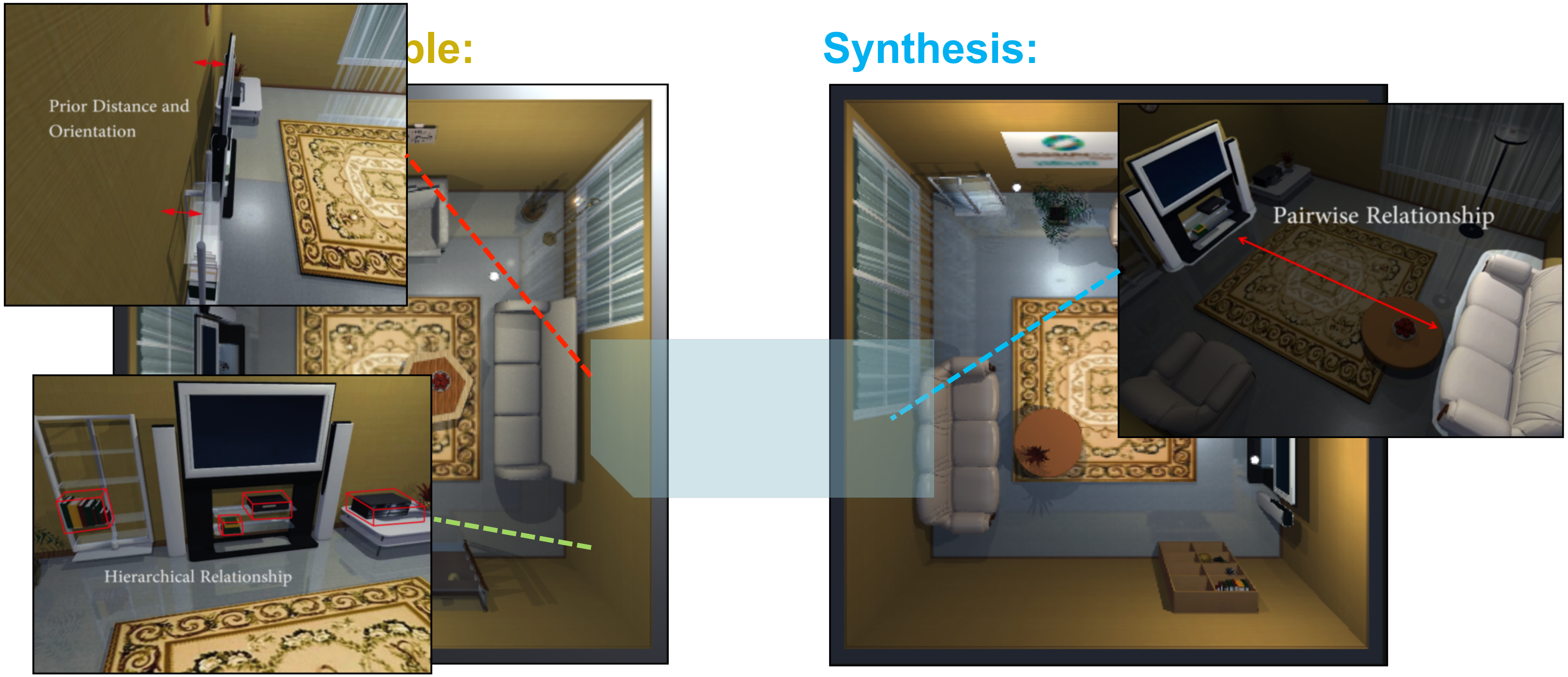
Advantages
- ✓ Ergonomics
- ✓ Interior design
- ✓ Automatic
- ✓ Many good solutions



Flowchart

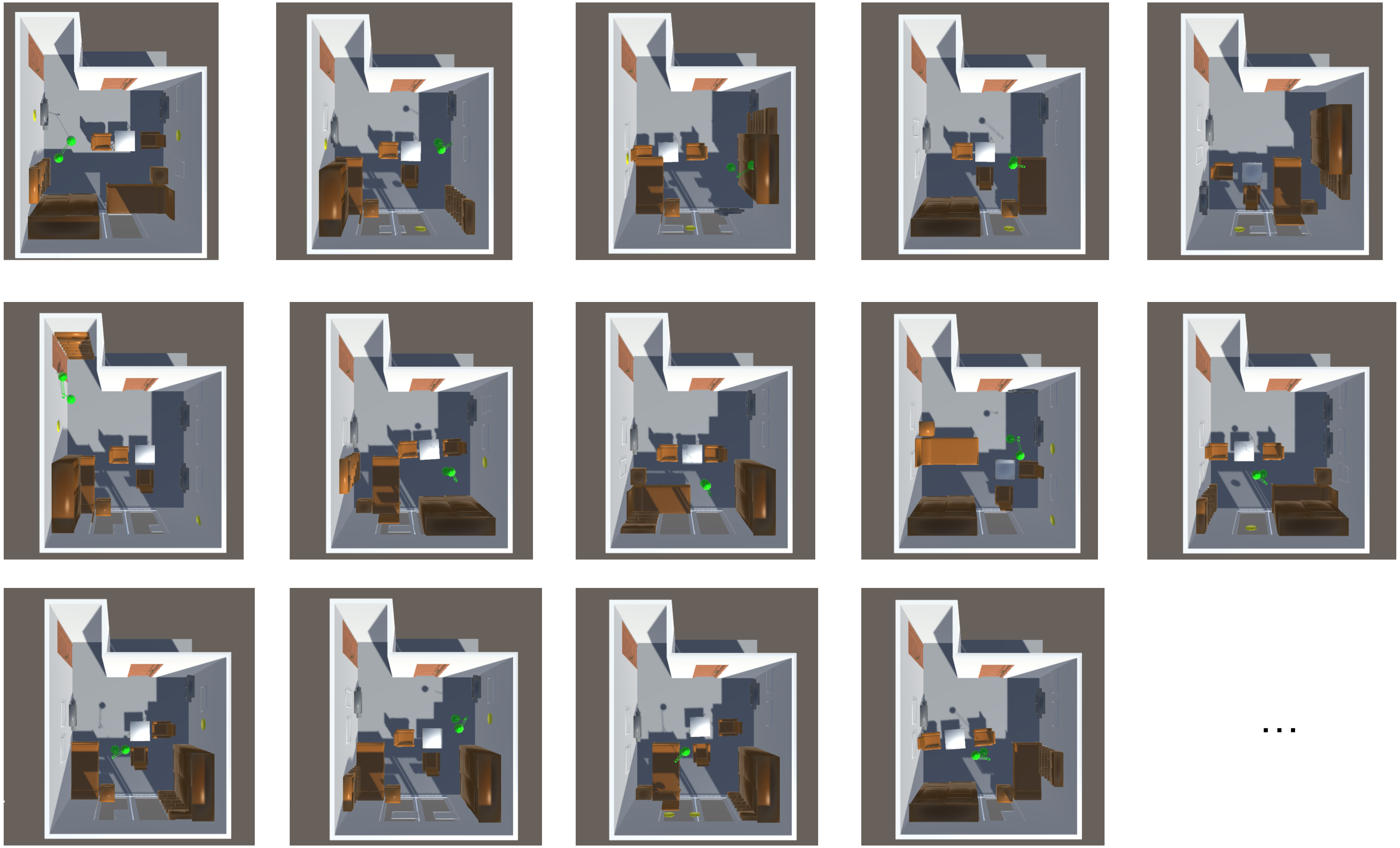

Extraction Step
Optimization Step
Positive Examples
Relationship Extraction:
1) Spatial
2) Hierarchical
3) Pairwise
Initialization
Cost-term Definitions
Update Scene by a Step
No
Terminate?
Yes
Synthesis Finished

Learning: Positive Examples



1. Identify useful features from data

Learning: Positive Examples

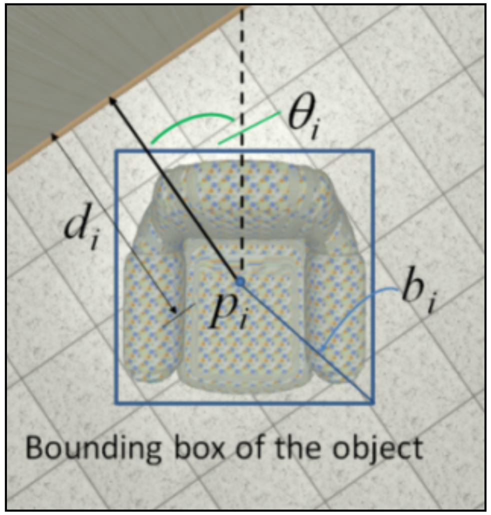


…

Optimization: Cost Terms

- Furniture arrangement: $\phi = \{(p_i, \theta_i) | i = 1 \ldots n\}$

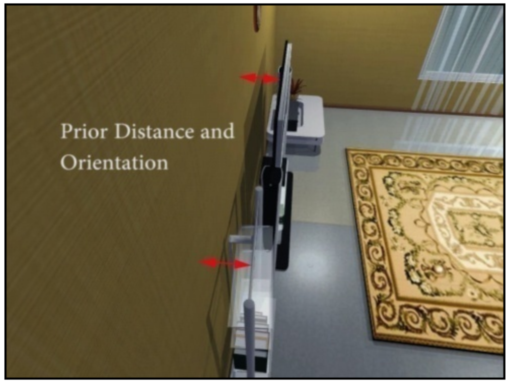
- Object notations:



Object Representation

Optimization: Cost Terms

1) Prior Distance Cost $C_{\text{pr}}^{d}(\phi) = \sum_i \| d_i - \bar{d}_i \|$
2) Prior Orientation Cost $C_{\text{pr}}^{\theta}(\phi) = \sum_i \| \theta_i - \bar{\theta}_i \|$
3) Prior Pairwise Distance Cost
   - similar to $C_{\text{pr}}^{d}(\phi)$
   - replace prior distance by pairwise distance $C_{\text{pair}}^{d}(\phi)$
4) Prior Pairwise Orientation Cost
   - similar to $C_{\text{pr}}^{\theta}(\phi)$
   - replace prior orientation by pairwise orientation $C_{\text{pair}}^{\theta}(\phi)$



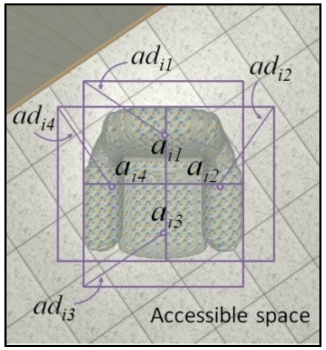
2. Represent useful features in a statistical model

Optimization: Cost Terms

5) Accessibility Cost $C_a(\phi)$

- penalizes as object i overlaps with object j's accessible space k

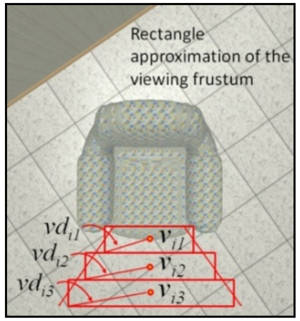
$$C_a(\phi) = \sum_i \sum_j \sum_k \max\left[0, 1 - \frac{\| p_i - a_{jk} \|}{b_i + ad_{jk}}\right]$$



6) Visibility Cost $C_v(\phi)$

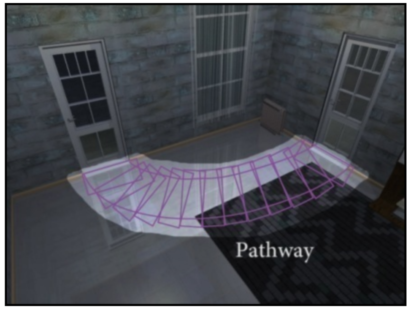
- penalizes as object i overlaps with object j's visibility approximation rectangle k

$$C_v(\phi) = \sum_i \sum_j \sum_k \max\left[0, 1 - \frac{\| p_i - v_{jk} \|}{b_i + vd_{jk}}\right]$$



7) Pathway Cost $C_{path}(\phi)$

- pathway approximated by rectangles along a cubic Bezier curve
- similar to $C_v(\phi)$



Optimization: What are we optimizing?

- Overall Cost: $C(\phi) = w_{\mathrm{a}} C_{\mathrm{a}}(\phi) + w_{\mathrm{v}} C_{\mathrm{v}}(\phi) + w_{\mathrm{path}} C_{\mathrm{path}}(\phi)$
$+ w_{\mathrm{pr}}^{d} C_{\mathrm{pr}}^{d}(\phi) + w_{\mathrm{pr}}^{\theta} C_{\mathrm{pr}}^{\theta}(\phi)$
$+ w_{\mathrm{pair}}^{d} C_{\mathrm{pair}}^{d}(\phi) + w_{\mathrm{pair}}^{\theta} C_{\mathrm{pair}}^{\theta}(\phi)$

- Same framework extended to 2nd tier objects, with 1st tier parents as the "room"

$$\phi = \{(p_i, \theta_i) | i = 1 \ldots n\}$$

3. Optimize w.r.t. statistical model and other criteria

Optimization: How to optimize?

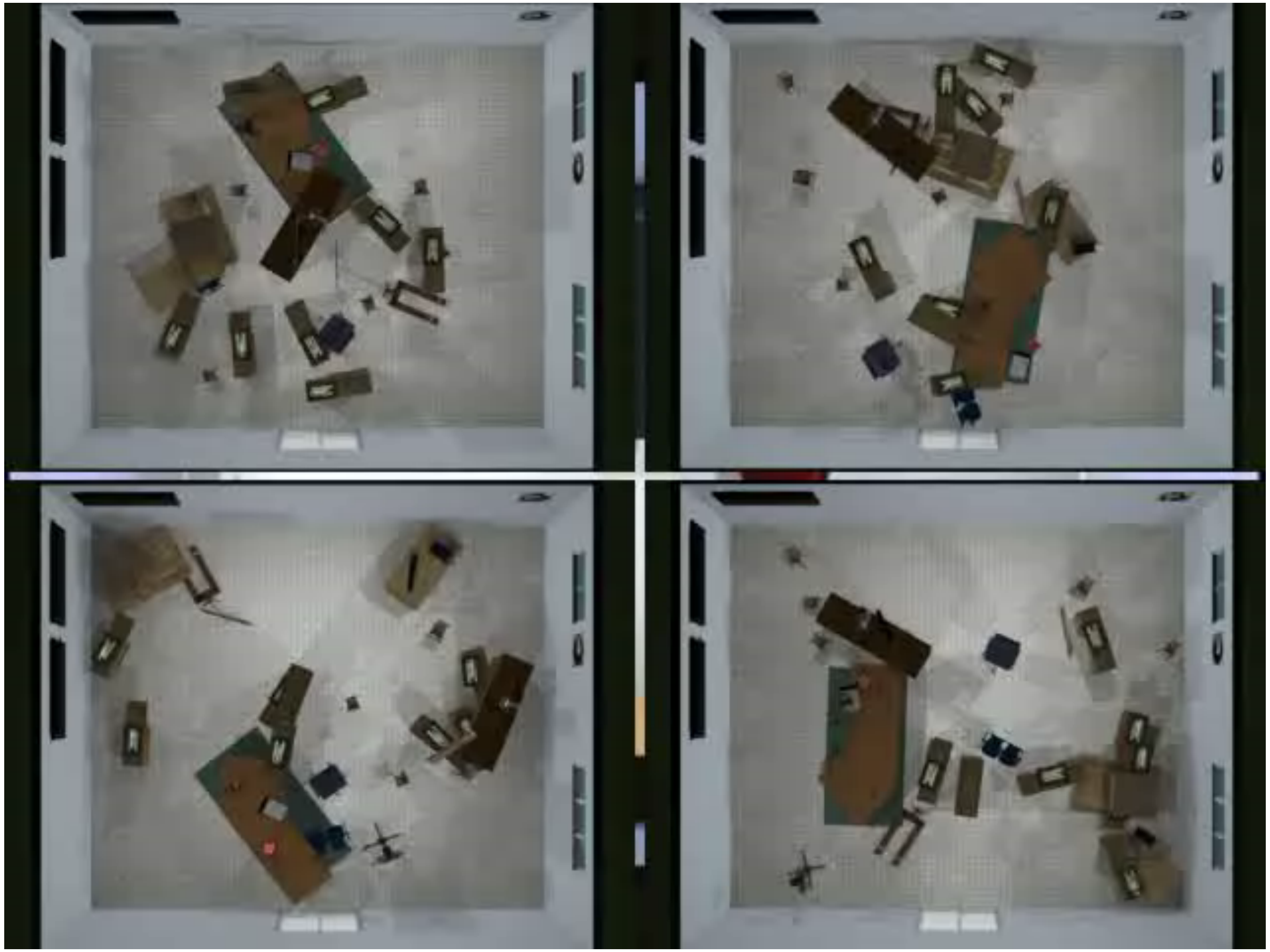
Simulated Annealing

- Computational imitation of physical annealing process

Cooling schedule:

- At the beginning, high temperature:
  → “heat up” furniture objects, allow flexible rearrangement
- Over time, temperature lowers gradually:
  → rearrangement is less aggressive
- At the end, temperature drops to zero:
  → refine final arrangement

Results: Iterations



4. Optimization result → Modeling result

Optimization: Simulated Annealing

At each iteration, a "move" is proposed,

- Transition: $\phi \rightarrow \phi'$
- Metropolis criterion determines transition probability: $f(\phi) = e^{-\beta C(\phi)}$

Transition probability:

$$\alpha(\phi' | \phi) = \min\left[\frac{f(\phi')}{f(\phi)}, 1\right]$$

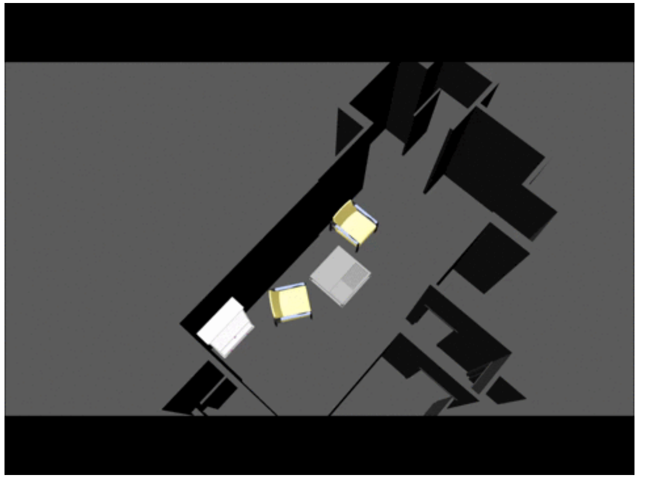
$$= \min\left[\exp(\beta(C(\phi) - C(\phi'))), 1\right]$$

,where $\beta \propto \dfrac{1}{Temperature}$

Optimization: Proposed Moves

- Translation
- Rotation
- Swapping Objects
- Moving Pathway Control Points
    - Similar to translation
    - Change pathway shape (a cubic Bezier curve)

Optimization: Proposed Moves



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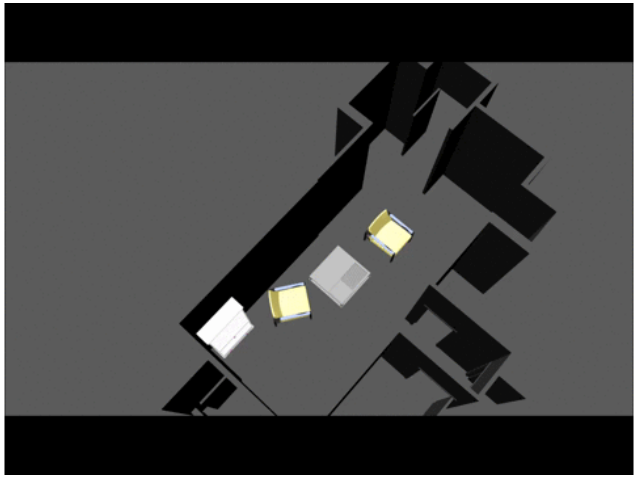

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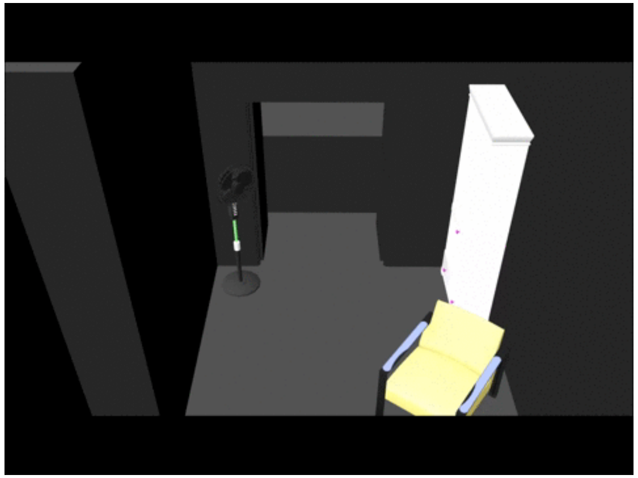

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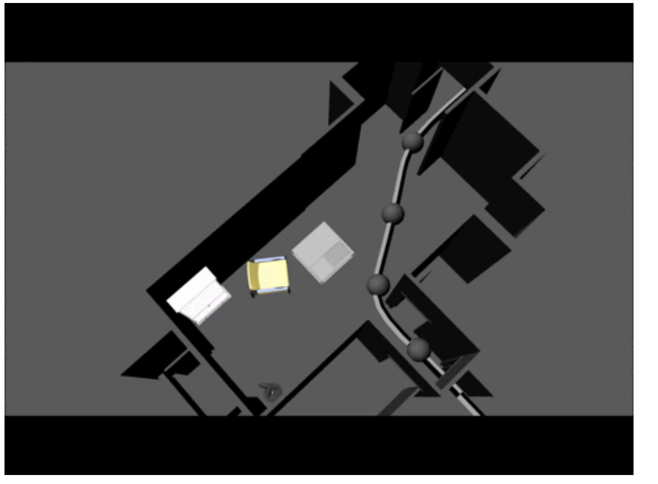


Results

Factory Example:

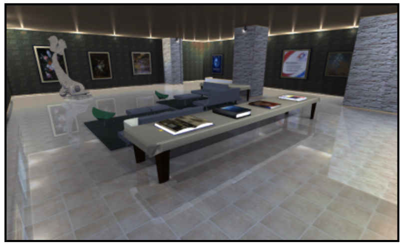
Synthesis:

Flower-shop Example:

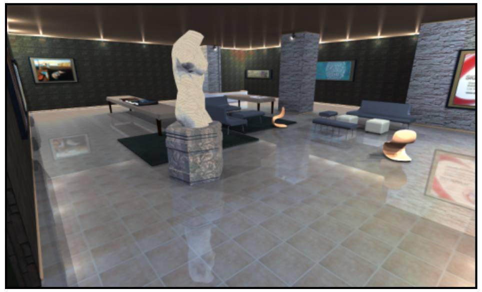
Synthesis:

Results

Gallery Example:



Synthesis:

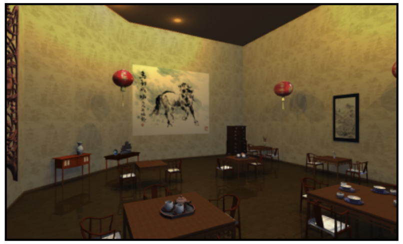


Resort Example:

Synthesis:

Results

Restaurant Example:



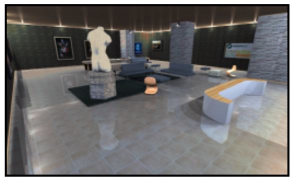
Synthesis:

Make it Home: Summary

Contributions:

- Data-driven optimization framework for interior design
- Incorporated human ergonomic criteria
- Extensible to other considerations
- Scalable through automation






Make it Home: Summary

Media attention

- NewScientist

StartUp Company

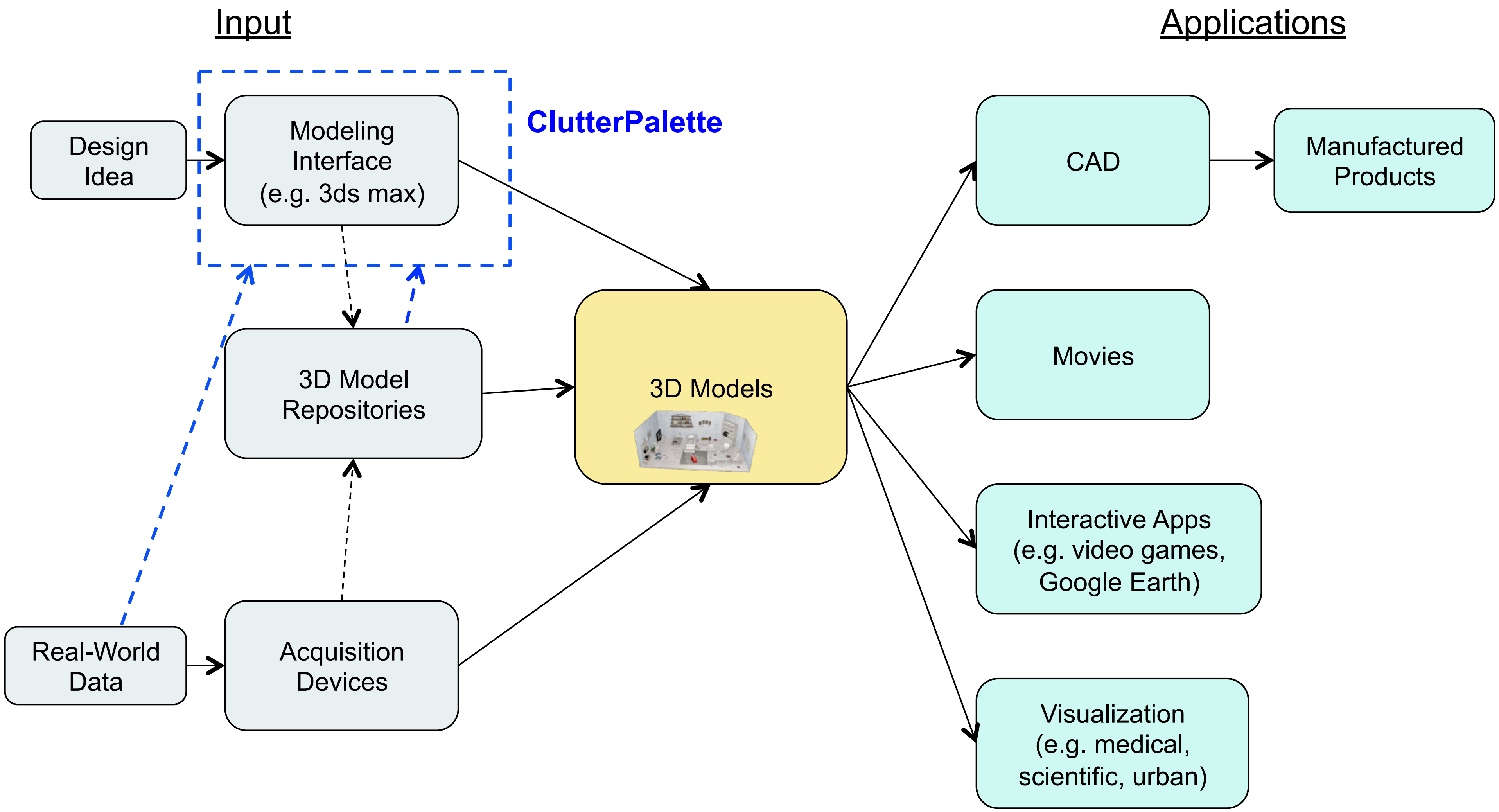
- SKY Optimum Technology Pte. Ltd.
  - Funded by angel investor
  - First product: MagixHome
  - http://www.skyopt.com

SKYOPT
SKY Optimum Technology Pte. Ltd.

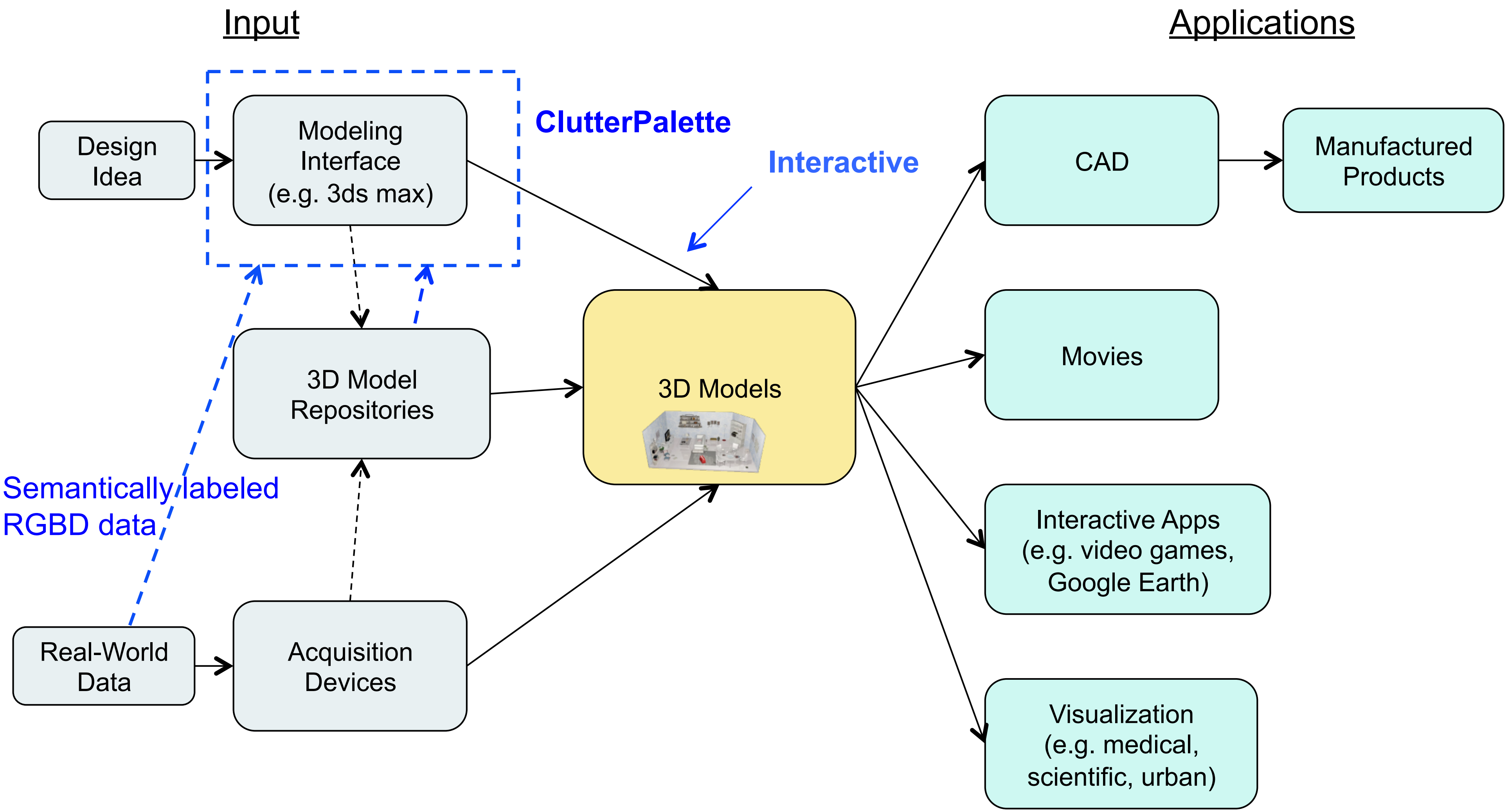
Scene Modeling

"The Clutterpalette: An Interactive Tool for Detailing Indoor Scenes", *IEEE TVCG 2015*
Lap-Fai Yu, Sai-Kit Yeung, Demetri Terzopoulos

The Big Picture: ClutterPalette



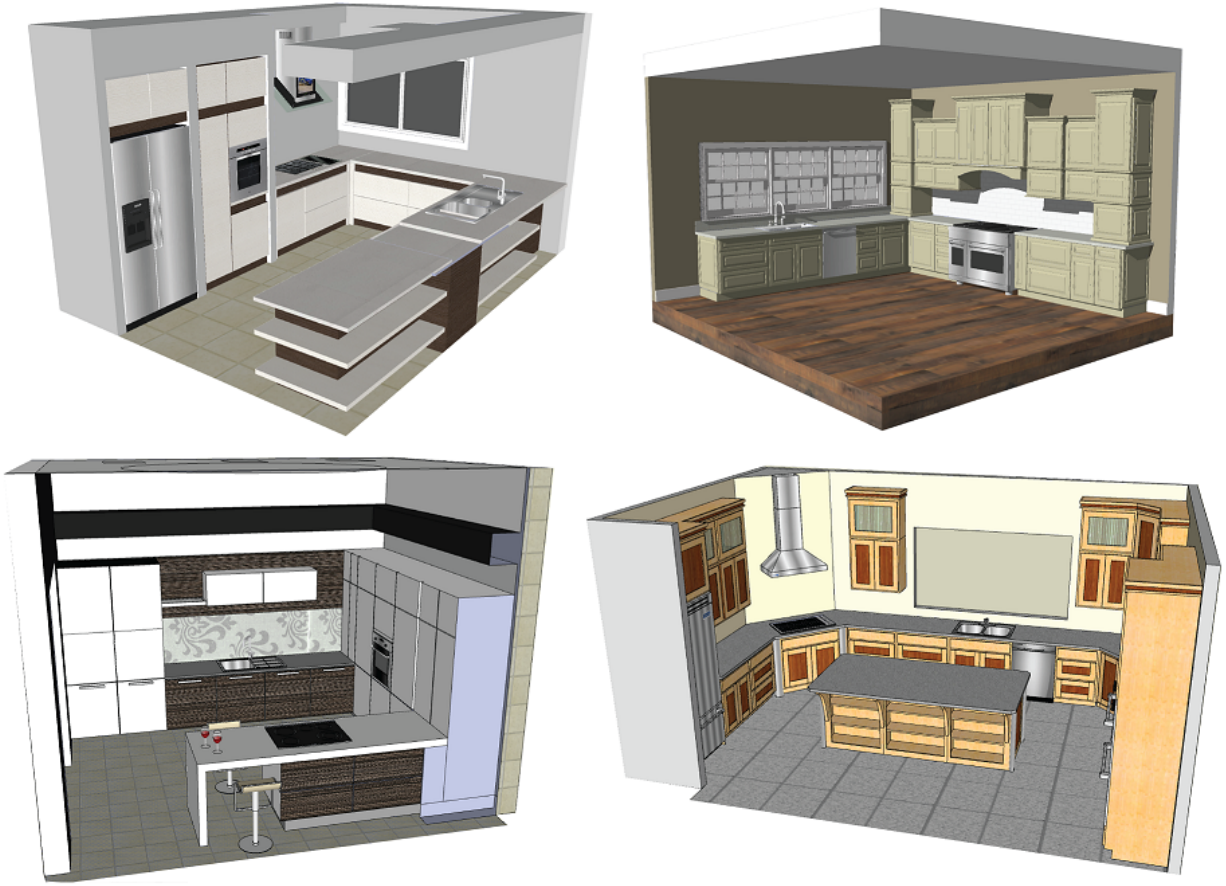
The Big Picture: ClutterPalette



Motivation

Virtual Indoor Scenes (Kitchen):

From Trimble 3D Warehouse



Motivation

Virtual Indoor Scenes (Kitchen):

From Trimble 3D Warehouse

Motivation

Common Indoor Scenes (Kitchen):

Motivation

Set Dressing: How to populate clutter objects?

- Scroll over a menu v.s. smart suggestion

Clutter Objects:

Indoor Scene:

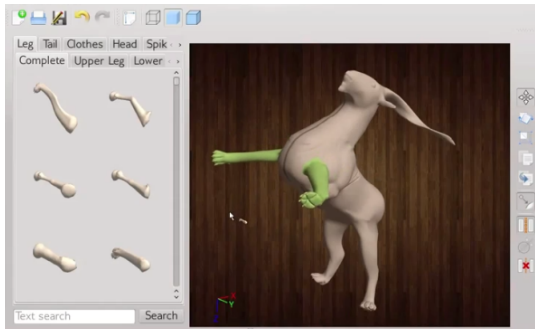
Related Work

Indoor Scene Modeling:

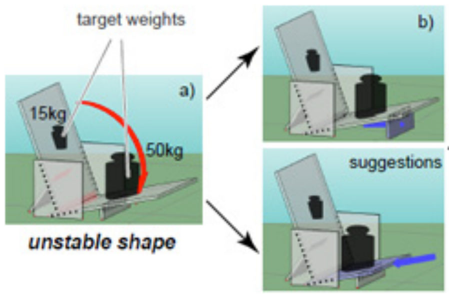
- [Bukowski and Sequin 1995], [Xu et al. 2002], [Merrell et al. 2011], [Yeh et al. 2012]
- [Fisher and Hanrahan 2010], [Yu et al. 2011], [Fisher et al. 2011], [Fisher et al. 2012]

Suggestive Interface:

- [Igarashi and Hughes 2001]
- [Chaudhuri et al. 2010; 2011], [Umetani et al. 2012]



[Chaudhuri et al. 2011]



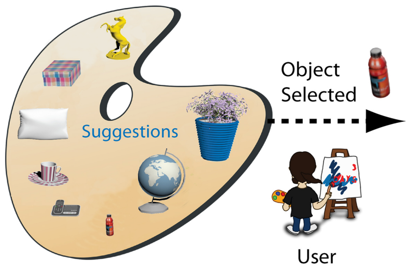
[Umetani et al. 2012]

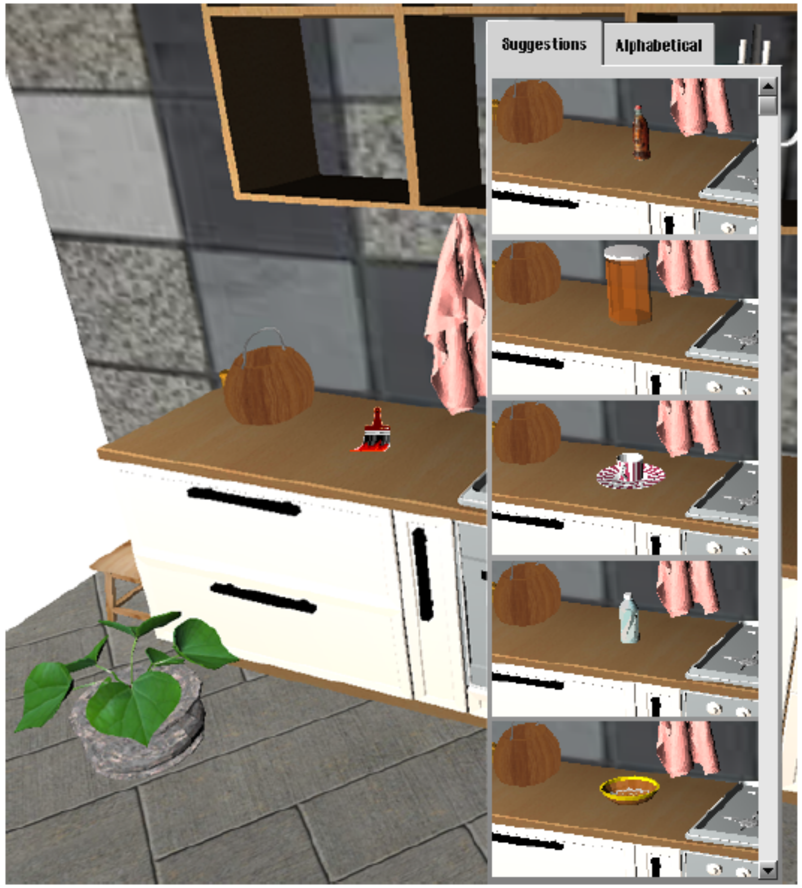
Overview

Input
- Room + cluttered objects

Output
- Set dressed room

Advantages
✓ Interactive tool
✓ Intuitive control
✓ Relevant suggestions
✓ Fast modeling

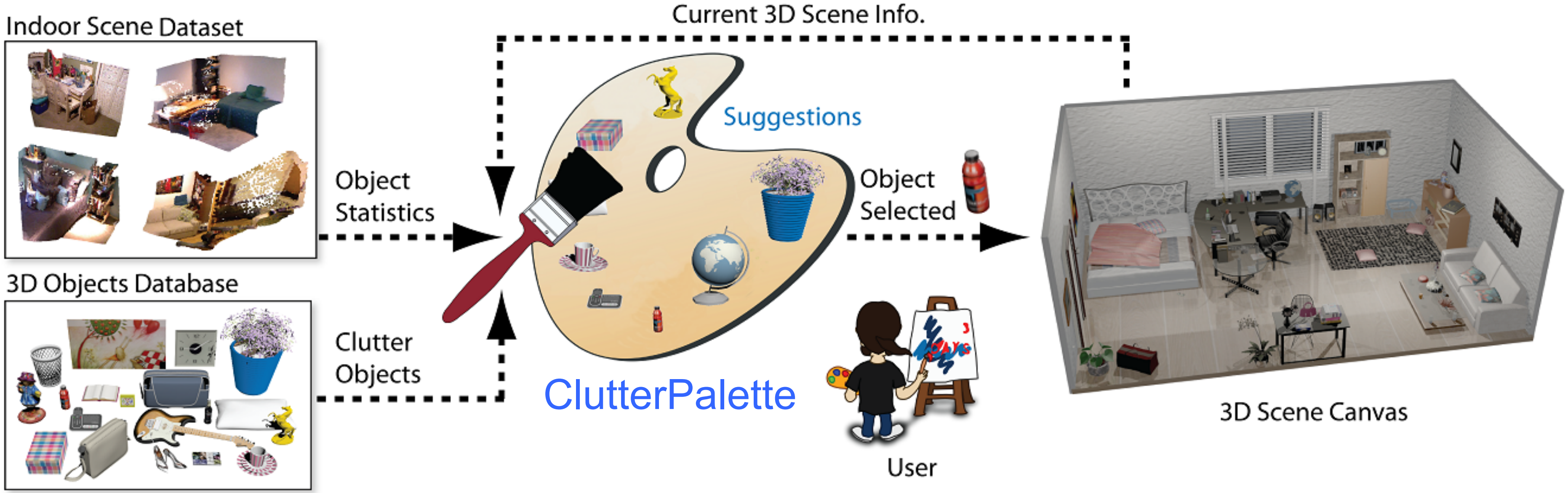




Make It Home v.s. ClutterPalette

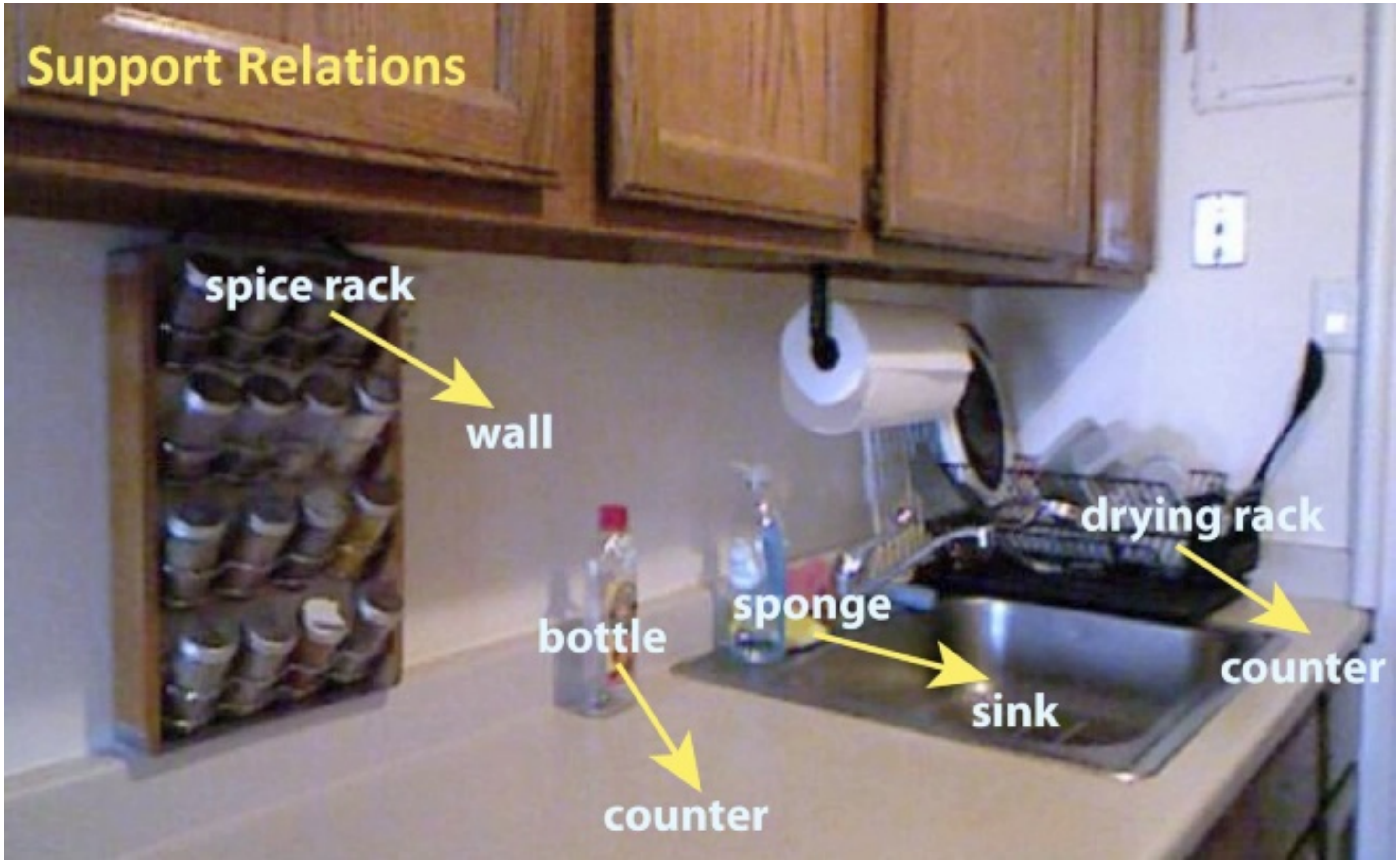
1) Automatic v.s. Interactive
2) Arrangement v.s. Placement
3) All the furniture objects are given v.s. only 1st tier object is given

Approach Overview



Data

Support relations from indoor scene images:



NYU Kinect Dataset V2

For details, [Silberman et al. 2012]

Statistics

Example excel files

	A	B	C	D	E	F	G	H	I	J
1		book	bottle	cabinet	ceiling	chair	cone	counter	dishwasher	faucet
2	book	88	0	0	0	0	0	0	0	0
3	bottle	1	0	1	0	0	0	0	0	0
4	cabinet	8	9	12	5	0	0	229	0	1
5	ceiling	0	0	5	8	0	0	0	0	0
6	chair	1	0	0	0	1	0	1	0	0
7	cone	0	0	0	0	0	0	0	0	0
8	counter	3	125	15	0	0	0	3	0	75
9	dishwasher	0	0	0	0	0	0	20	0	0
10	faucet	0	0	4	0	6	0	0	0	0
11	fire extinguish	0	0	0	0	0	0	0	0	0
12	floor	11	0	436	5	813	0	9	58	0
13	garbage bin	0	0	1	0	0	0	0	0	0
14	microwave	0	0	0	0	0	0	0	0	0
15	paper towel di	0	0	0	0	0	0	0	0	0
16	paper	6	0	0	0	0	1	0	0	0
17	pot	0	0	0	0	0	0	0	0	0
18	refridgerator	0	9	0	0	0	0	0	0	0
19	stove burner	0	0	0	0	0	0	0	0	0
20	table	60	22	0	1	3	0	0	0	0
21	unknown	0	0	1	0	0	0	1	0	0
22	wall	0	1	174	88	3	0	13	0	0
23	bowl	0	0	0	0	0	0	0	0	0
24	magnet	0	0	0	0	0	0	0	0	0

Supporter frequency

Suggestion Generation

Probabilistic Evaluation: $P(x = Y^i | w, s, \{n^j\})$

- Y^i : evaluated clutter type
- w : scene type (e.g. kitchen)
- s : supporter type (e.g. shelves)
- $\{n^j\}$: existing neighbor object types

$$
\begin{aligned}
&= \frac{P(x = Y_i) P(w, s, \{n_j\} | x = Y_i)}{P(w, s, \{n_j\})} \\
&\propto P(x = Y_i) P(w, s, \{n_j\} | x = Y_i) \\
&= P(x = Y_i) P(w | x = Y_i) P(s | x = Y_i) \\
&\qquad \prod_j P(n_j | x = Y_i).
\end{aligned}
$$

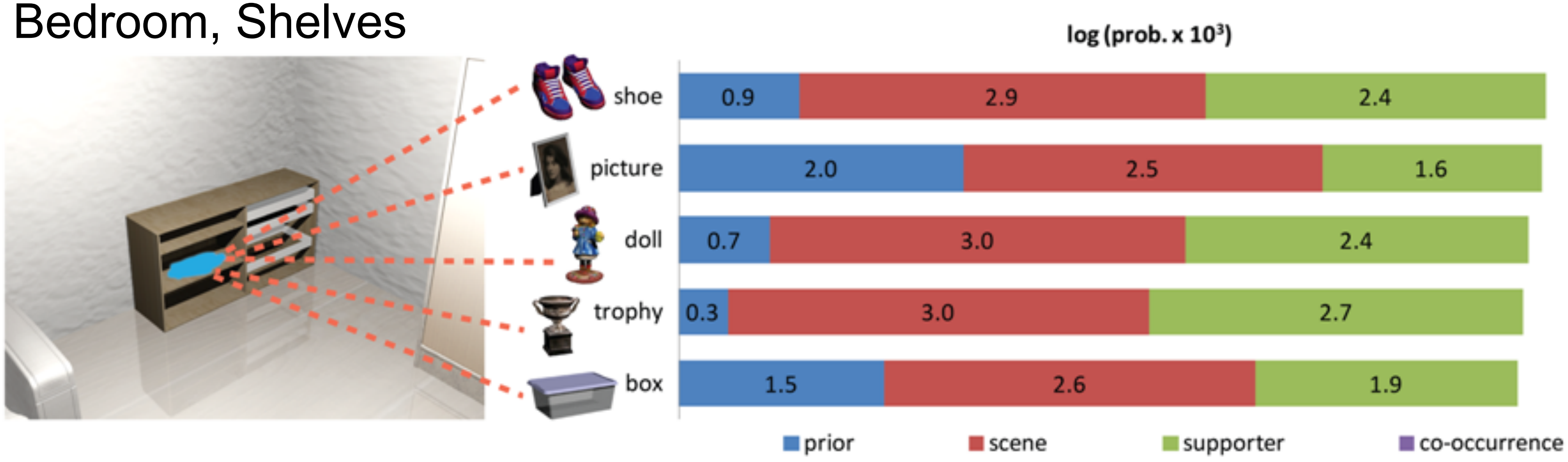
Probabilistic terms:

- Prior probability
- Conditional scene probability
- Conditional supporter probability
- Co-occurrence probability

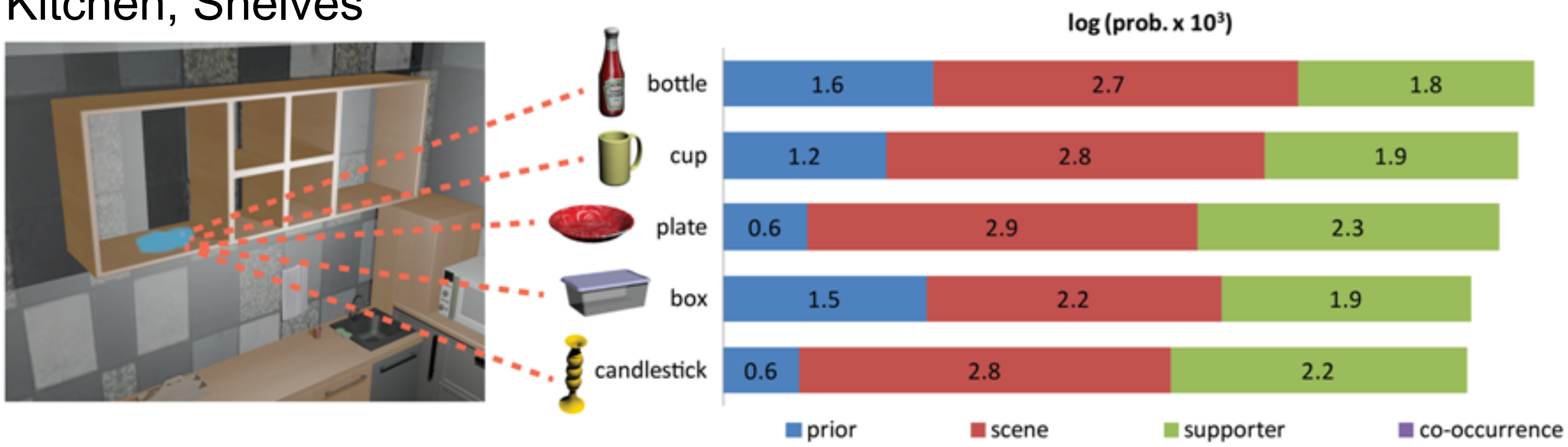
1. Identify useful features from data
2. Represent useful features in a statistical model

Same Supporter, Different Scenes

Bedroom, Shelves

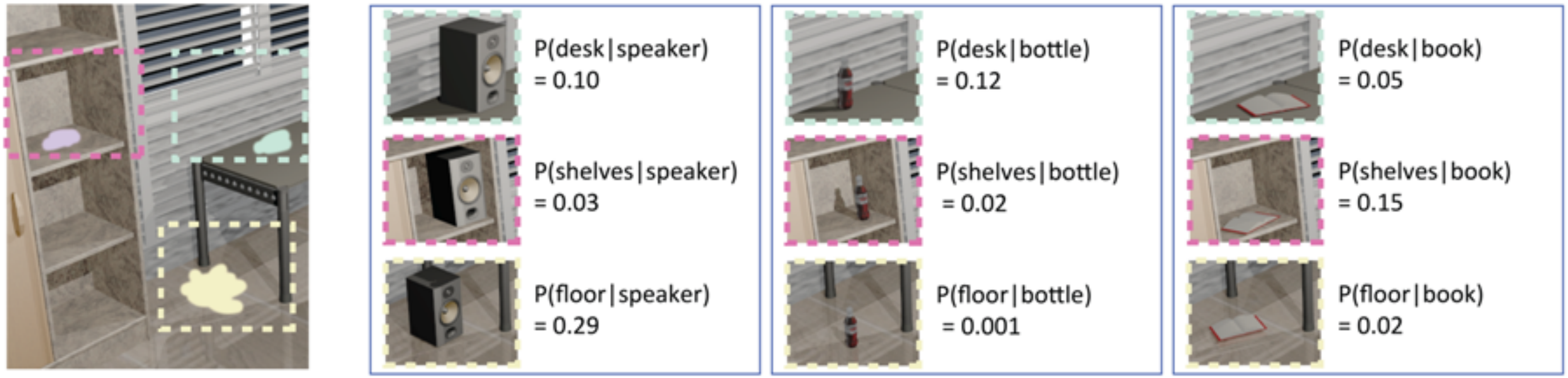


Kitchen, Shelves



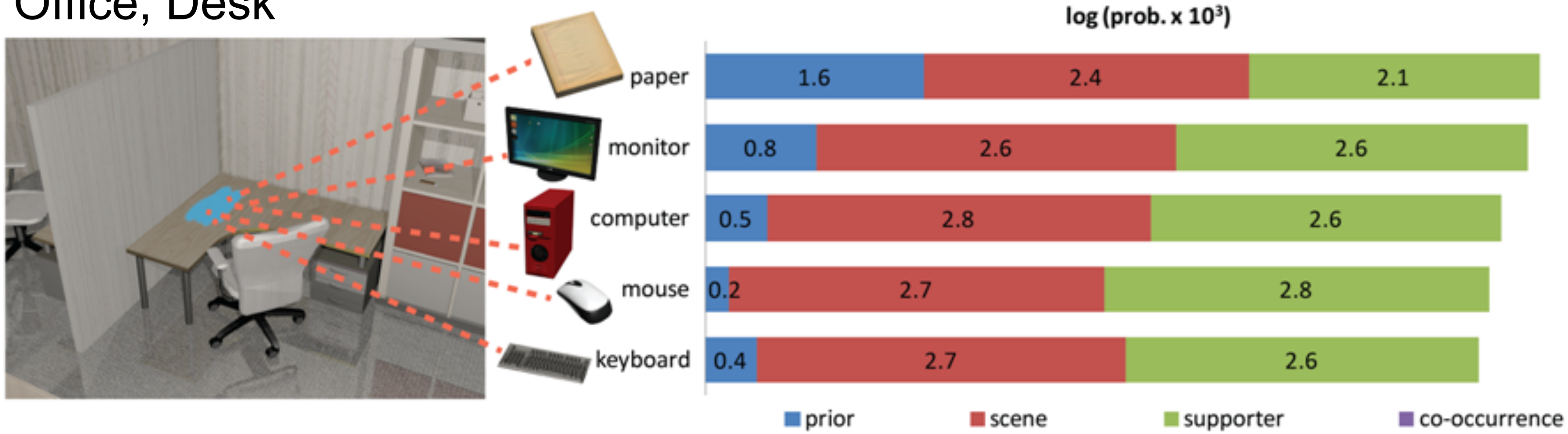
Same Scene, Different Supporters

Bedroom, {desk, shelves, floor}

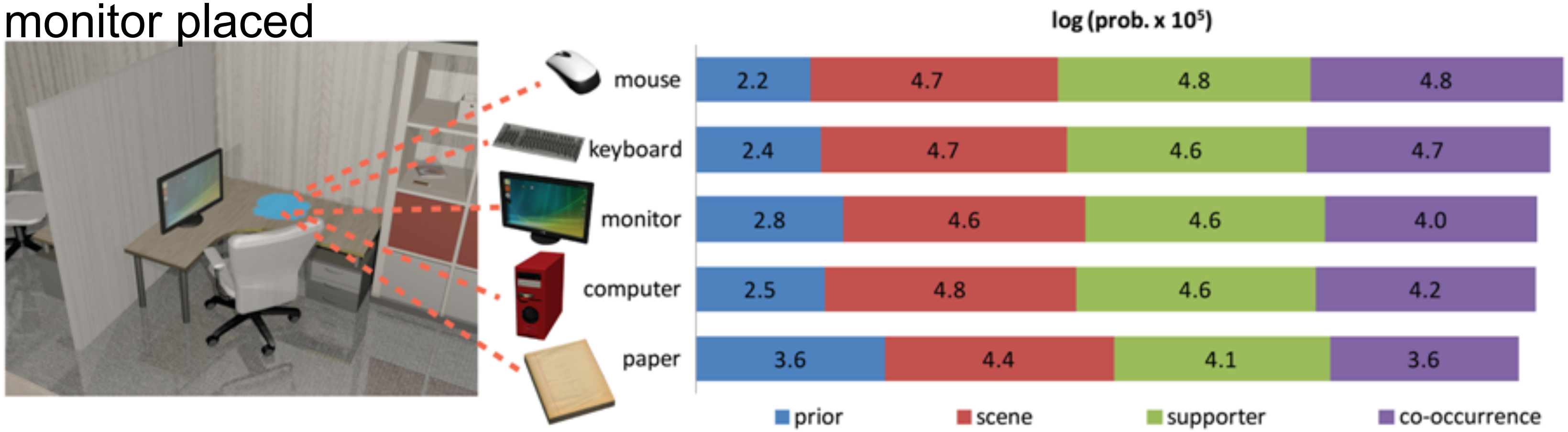


Co-occurrence

Office, Desk



Office, Desk, with monitor placed



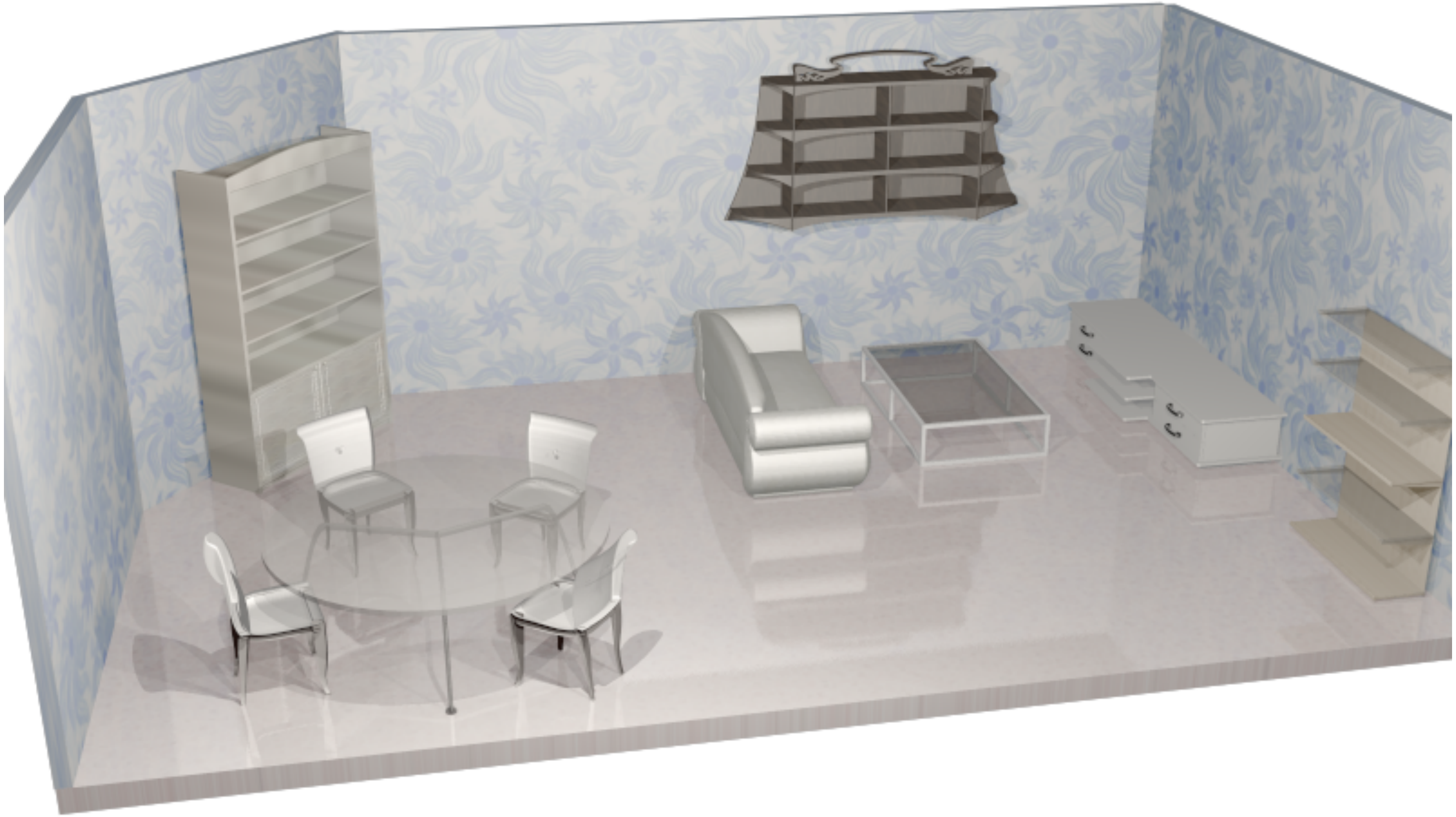
Demo

Demo: Result

Results: Bedroom

Results: Kitchen

Results: Living Room



Results: Office

Results: Classroom

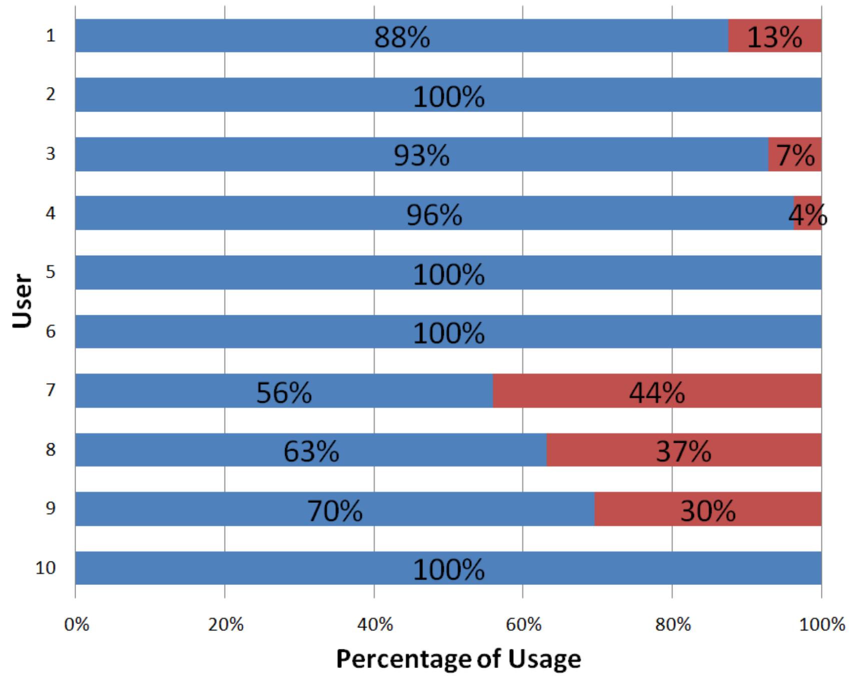
Usability Test

Modeling Speed (time between object addition):

- With the ClutterPalette: 22.25sec
- Without the ClutterPalette: 33.17sec
- Improvement: ~33%

Usage Frequency

- 87% of time



Make It Home v.s. ClutterPalette

1) Automatic v.s. Interactive
2) Arrangement v.s. Placement
3) All the furniture objects are given v.s. only 1st tier object is given
4) Statistics from virtual 3D models v.s. statistics from real world images

ClutterPalette: Summary

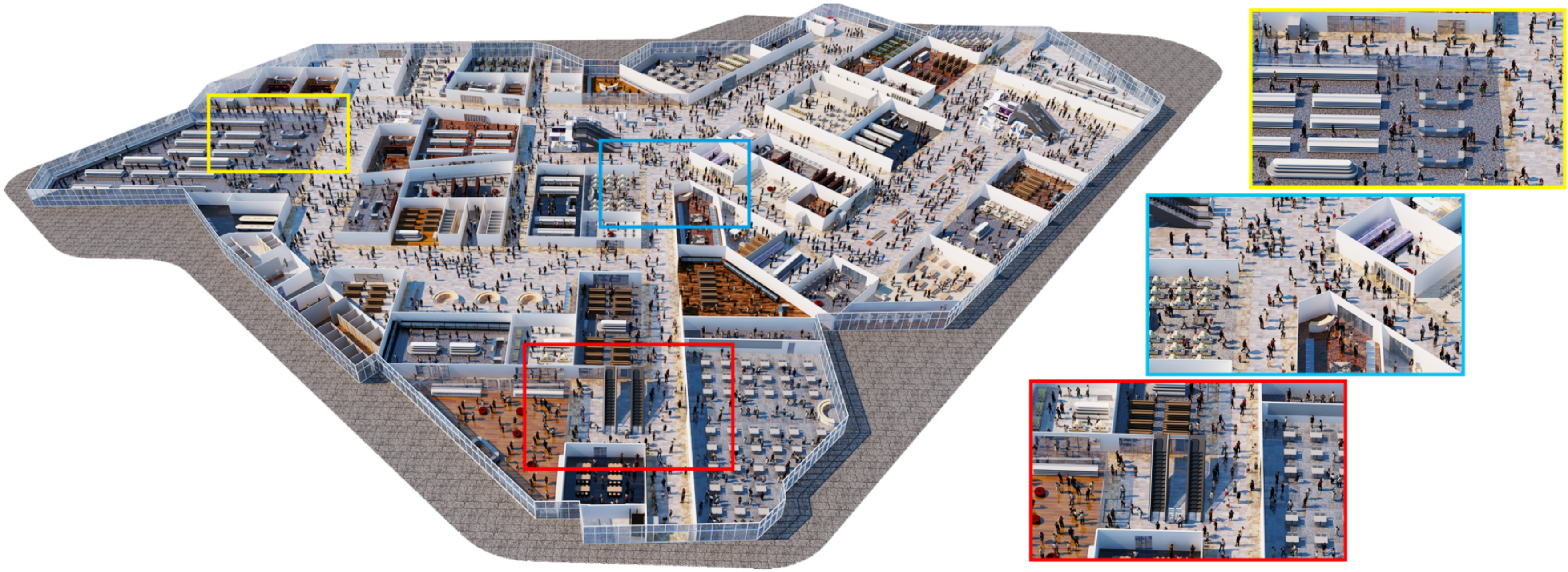
Contributions

- Proposed a novel direction of incorporating real-world scene statistics into an interactive scene modeling tool
- Demonstrated the capability of *the ClutterPalette* in modeling different common indoor scenes
- Validated the efficacy of *the ClutterPalette* in improving modeling speed and realism by a usability study

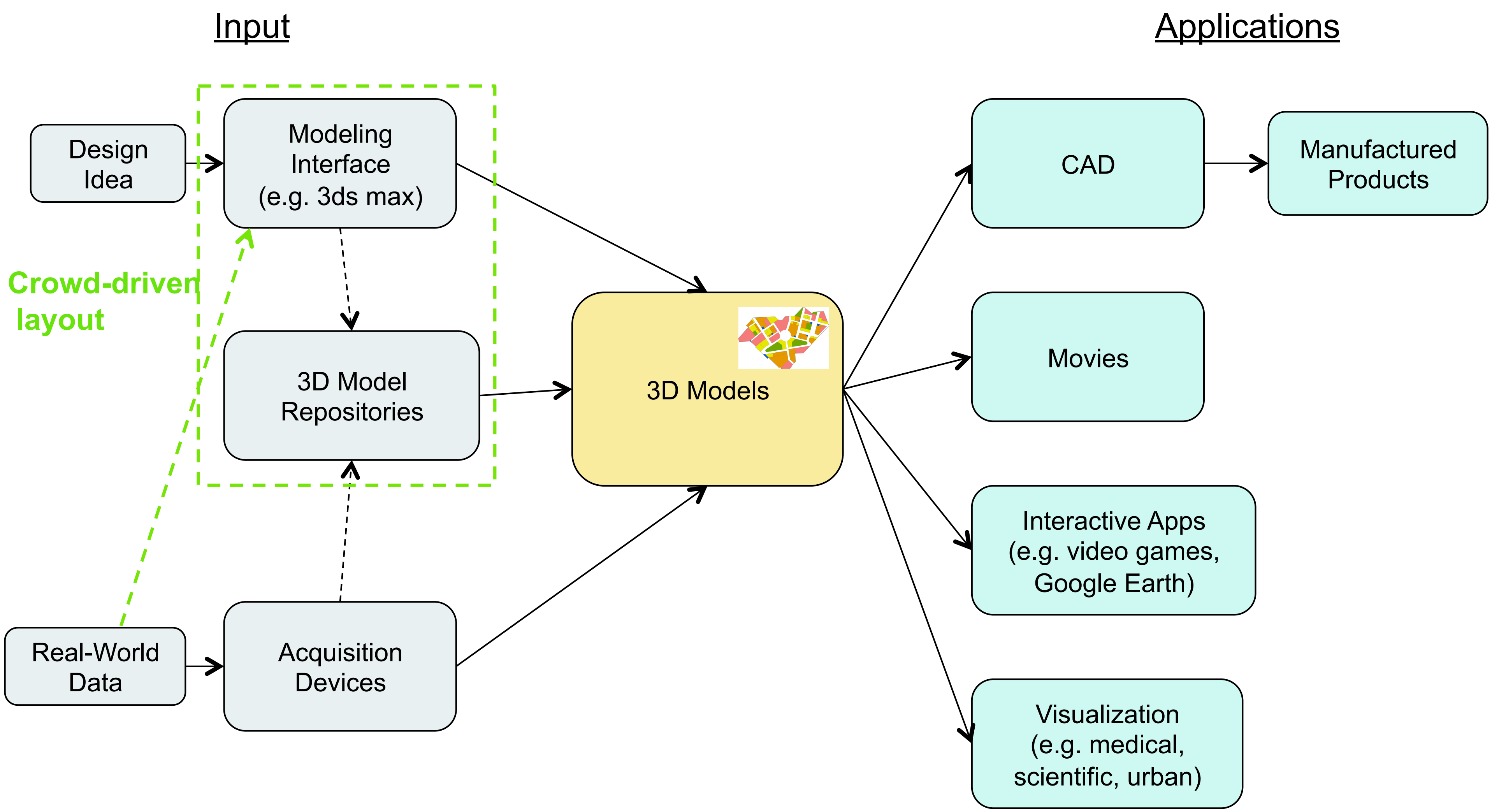
Scene Modeling

"Crowd-driven Mid-scale Layout Design", *ACM SIGGRAPH 2016.*

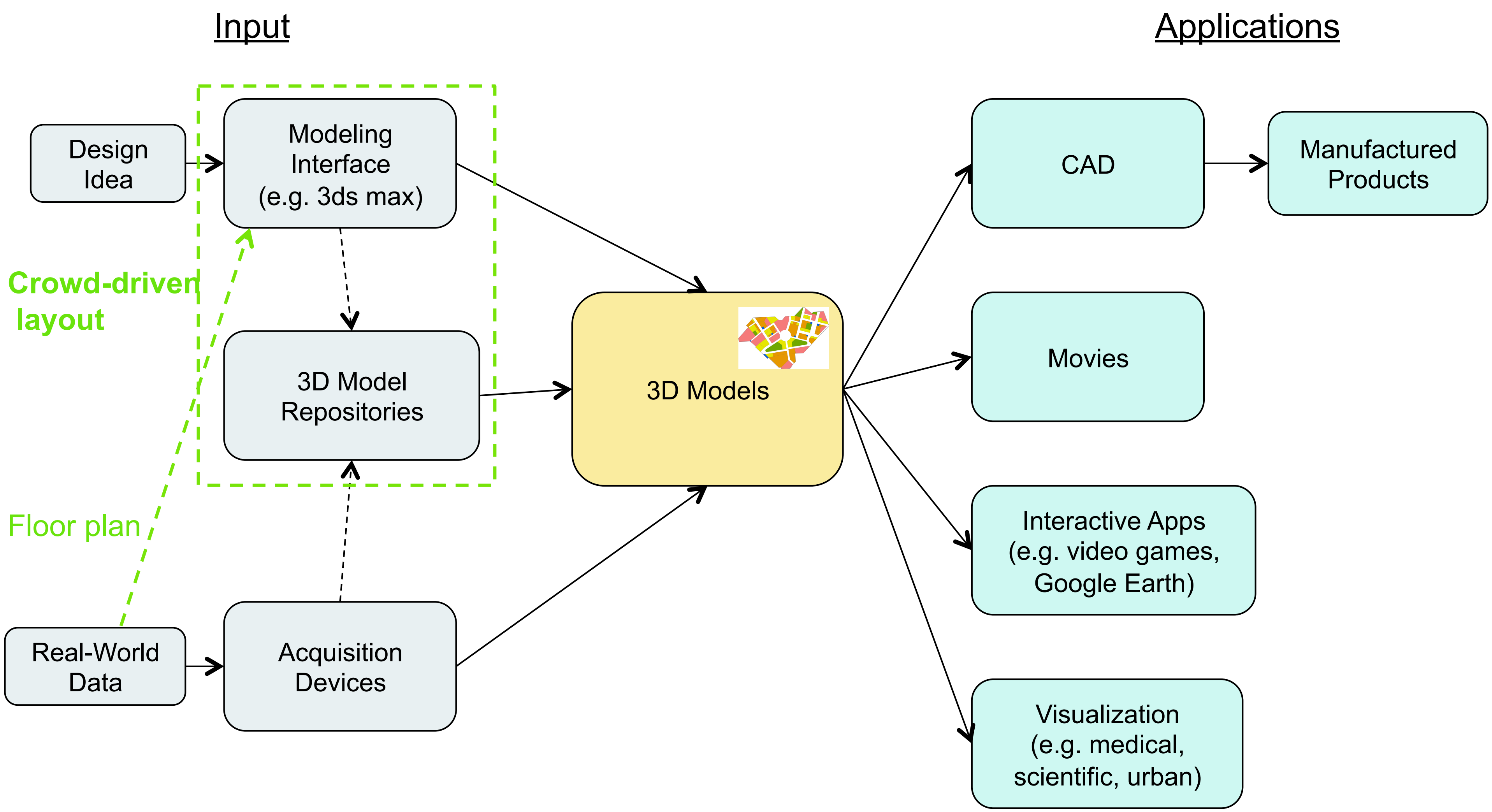
Feng Tian, Lap-Fai Yu, Sai-Kit Yeung, KangKang Yin, Kun Zhou



The Big Picture: Crowd-driven layout

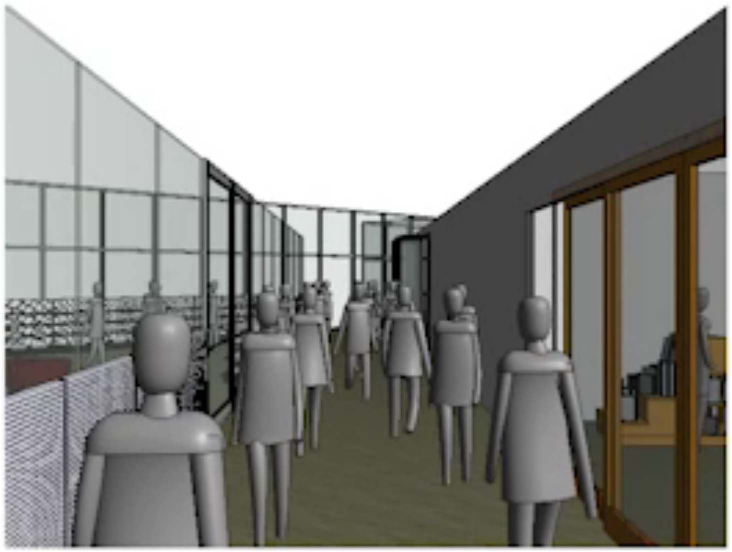


The Big Picture: Crowd-driven layout

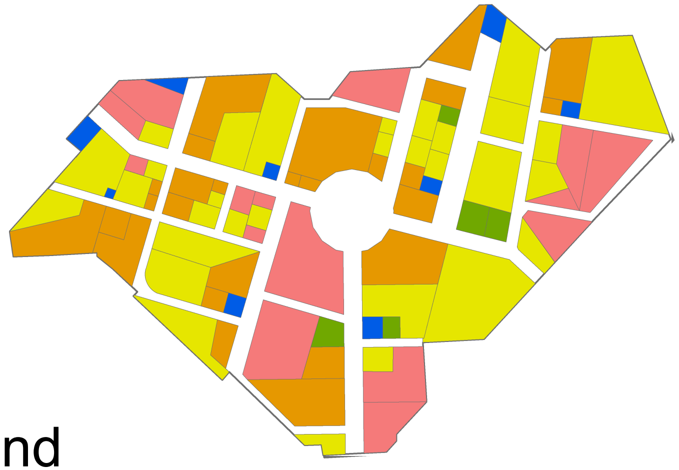


Motivation

Human flow is an important factor in layout design



Overview



Input

- Layout domain

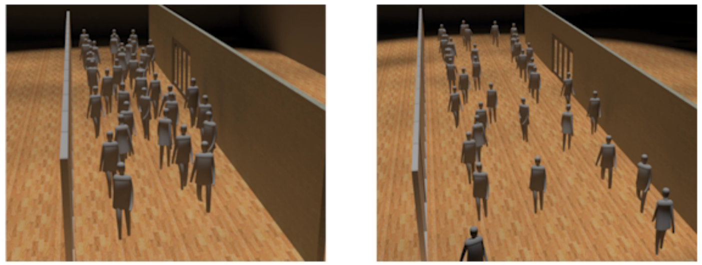
Output

- Layout optimized with agents' comfort and ease of movement

Features

- ✓ Suggest type and arrangement simultaneously
- ✓ Agent based model
  - ✓ Mobility cost
  - ✓ Accessibility cost
  - ✓ Coziness cost

Mobility cost



Crowd Driven Layout Design

1) Automatic + Interactive
2) Arrangement + Placement
3) All the “shop type” is given
4) Statistics from virtual 3D models (simulation)
 + statistics from real world design (“shop type”)

Demo

User Interface

Demo

User Interaction

Outline

Introduction

Motivation

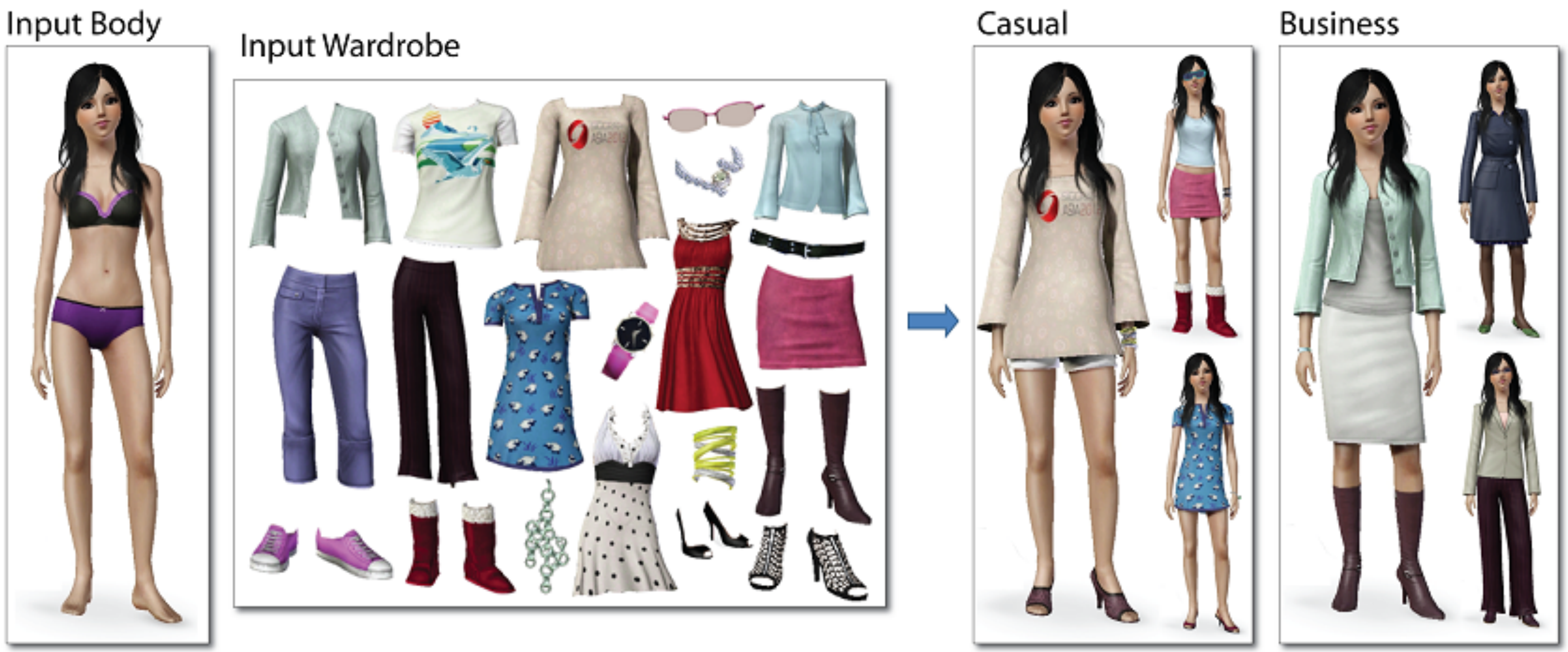
Research showcases

- Scene Modeling
- **Character Modeling**
- Shape Modeling

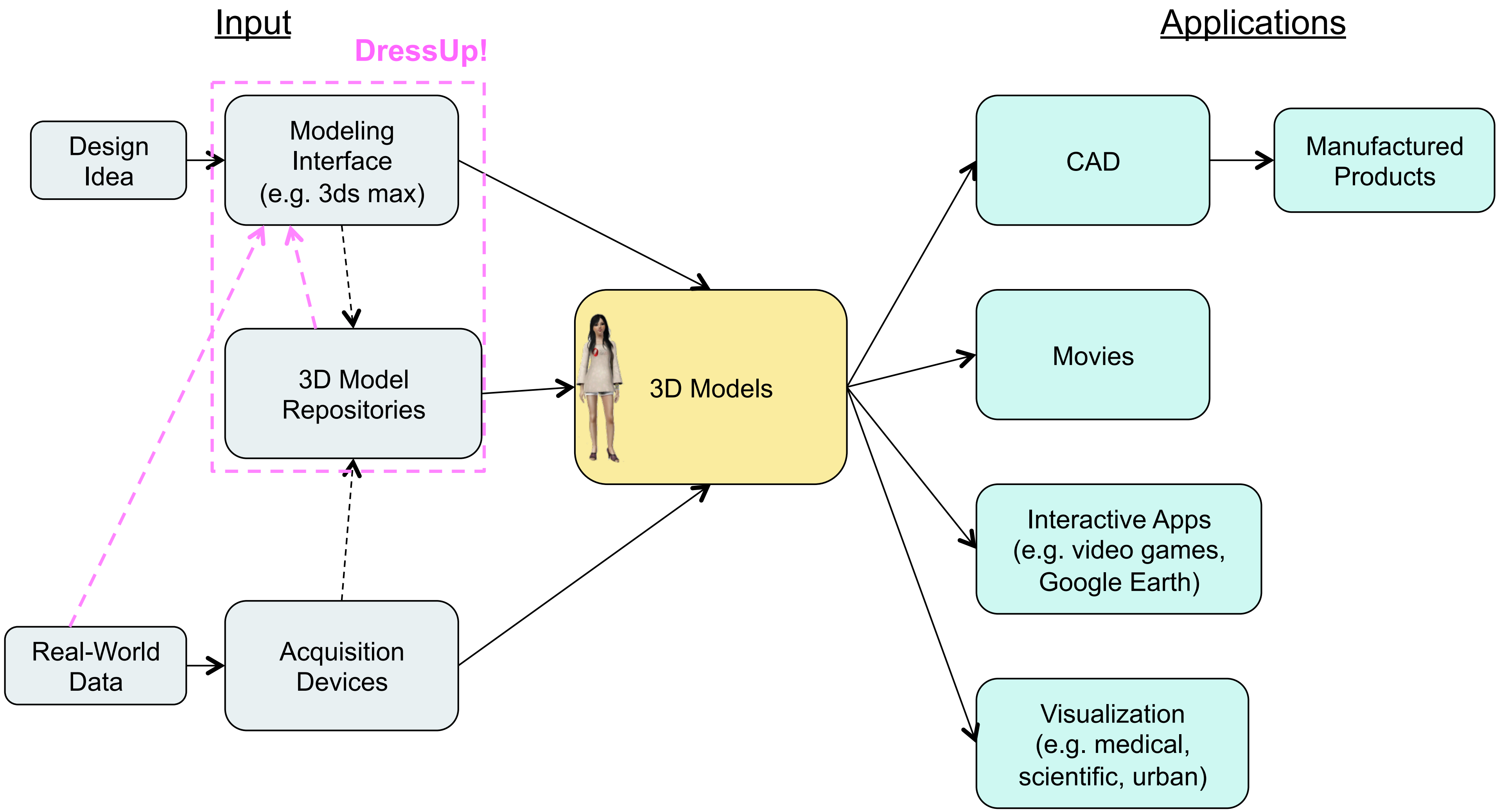
Conclusion

Character Modeling

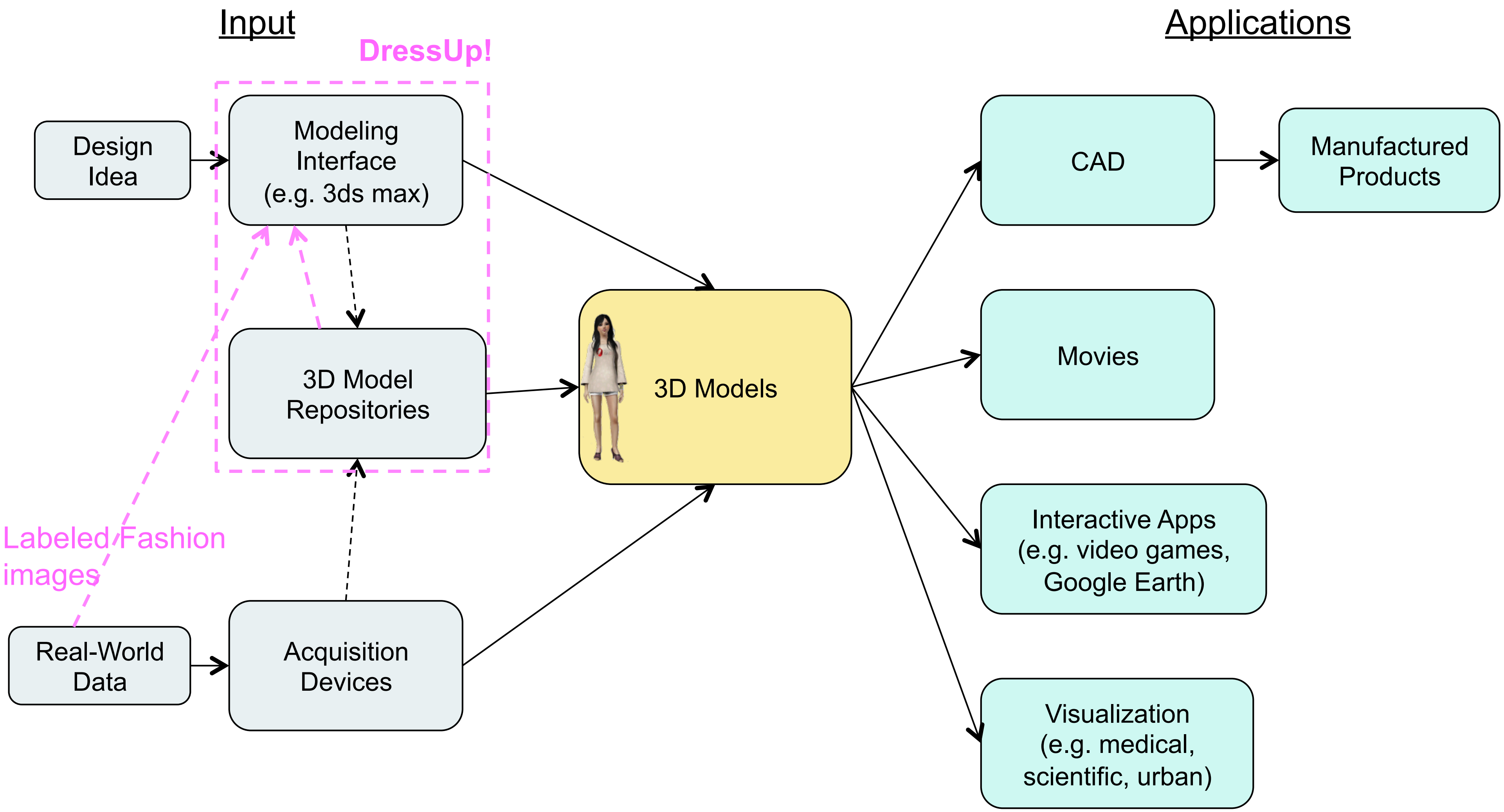
"DressUp! Outfit Synthesis through Automatic Optimization", *ACM SIGGRAPHAsia 2012*
Lap-Fai Yu, Sai-Kit Yeung, Demetri Terzopoulos, Tony F. Chan



The Big Picture: DressUp



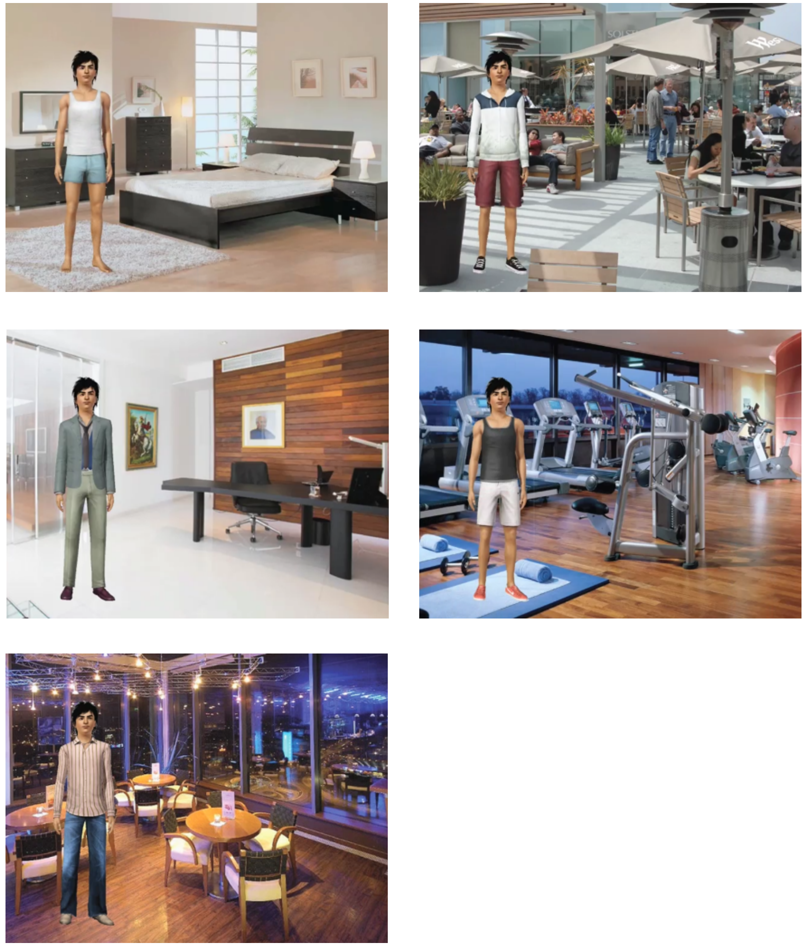
The Big Picture: DressUp



Motivation

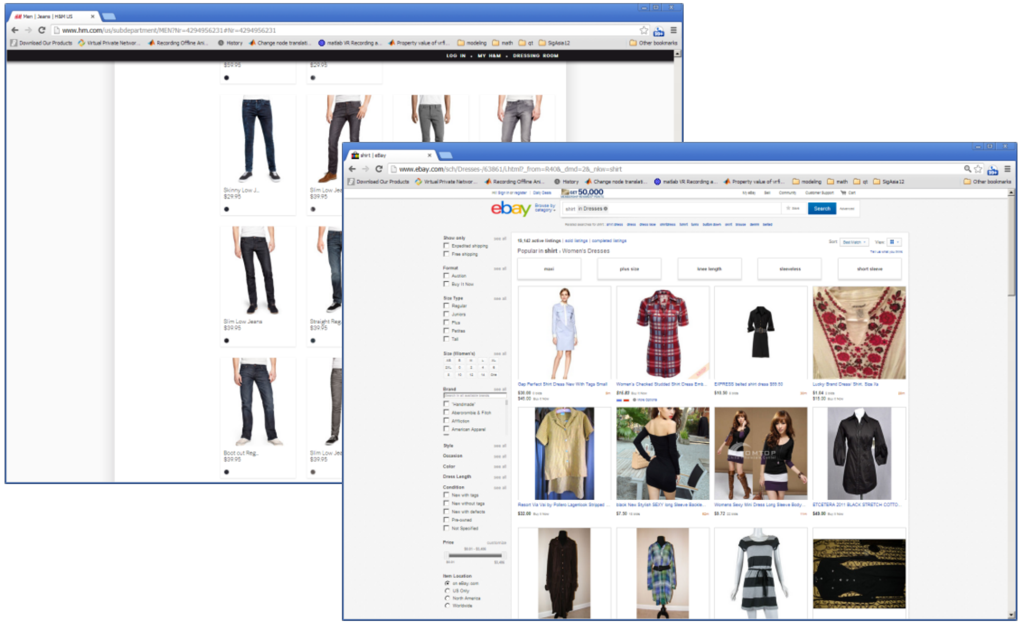
- Everyday Dressing
- Occasion Dependent

A day in the life



Motivation

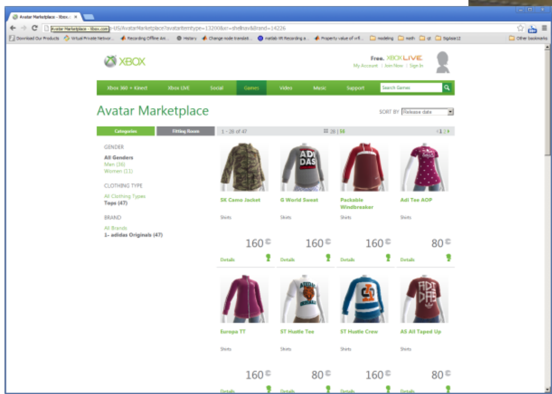
- Online shopping
- Boutiques



From Ebay & H&M

Motivation

- Virtual Character Modeling
  - generate non-player characters (e.g. crowd scene)
  - generate suggestions in character modeling UI

From DQ3, GTA5, xbox.com, Playstation HOME

Related Work

Clothing in CG

- modeling, rendering, animation
- interactive interfaces
- data-driven approaches

[Terzopoulos et al. 1987]

Crowd Modeling

- creating crowd variety
- crowd perception

[McDonnell et al. 2008]

Related Work

Fashion Literature

Style

- rules from social norm
- e.g. jeans + t-shirt, *not* dress-pants + t-shirt
- dependant on occasion /**dress code**

60’s hippies

Color

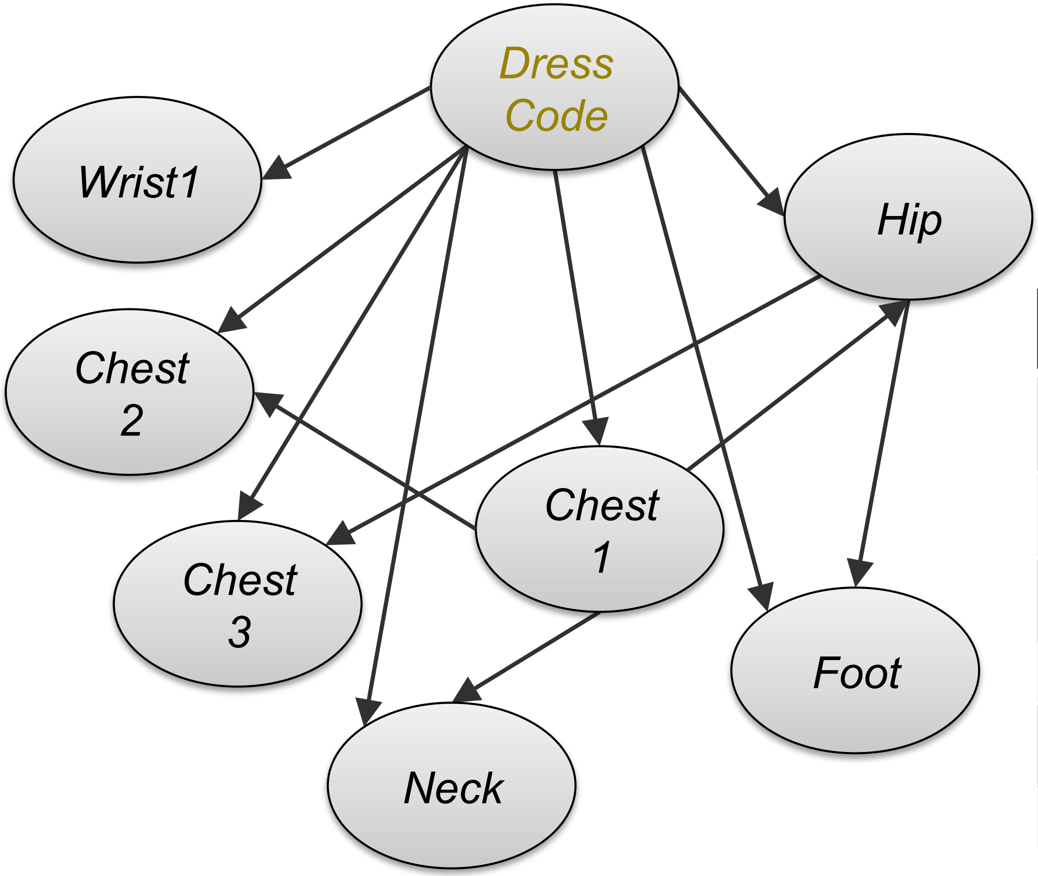
- classify body color tone (e.g. “warm”/”cool”, “4 seasons”)
- suggest **color palette** for clothing
- e.g. some people look good in bright colors

Make It Home v.s. DressUp!

1) Spatial domain v.s. Body domain
2) Furniture objects v.s. Clothing objects
3) All the furniture objects are given v.s. all the clothing objects are given

Style Learning

Example **Bayesian Network** for Men



Example Node	Example State
Dress Code	Casual, Sportswear, Business, Business-Casual
Chest1	T-shirt, Dress Shirt, Sleeveless
Chest2	Tank, Sweater, Vest, Long t-shirt
Hip	Jeans, Shorts, Dress Pants
Foot	Slippers, Dress Shoes, Boots
…	...

Style Learning

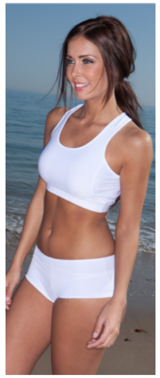
- Use labeled fashion images
- Learn BN structures and probabilities

search key: "man, business"



Dress Shirt Suit Jacket Tie Dress Pants Dress Shoes	Dress Shirt Vest Suit Jacket Tie Dress Pants	Dress Shirt Suit Jacket Dress Hat Tie Dress Pants

search key: "woman, sportswear"


Hoodie Sport Pants Cap Ear Rings Hand Wrap	Top Shorts	Tank Sport Pants Socks

Video

DressUp!
Outfit Synthesis Through
Automatic Optimization

Lap-Fai Yu[1] Sai-Kit Yeung[2]
Demetri Terzopoulos[1] Tony F. Chan[3]

[1]University of California, Los Angeles
[2]Singapore University of Technology and Design
[3]Hong Kong University of Science and Technology

DressUp!: Summary

Novelty

- introduced a new, highly practical topic area

Approach

- proposed a data-driven approach to learn outfit relationships
- formulated outfit synthesis as an optimization problem

Experiments

- demonstrated practicality for various applications

Validation

- validated efficacy by a gender-specific perceptual study

Outline

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- **Shape Modeling**

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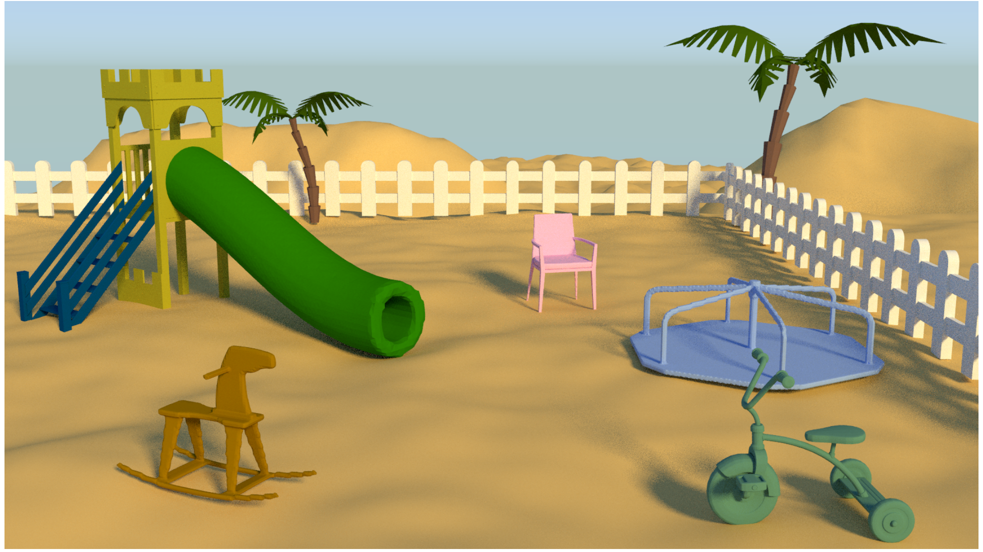
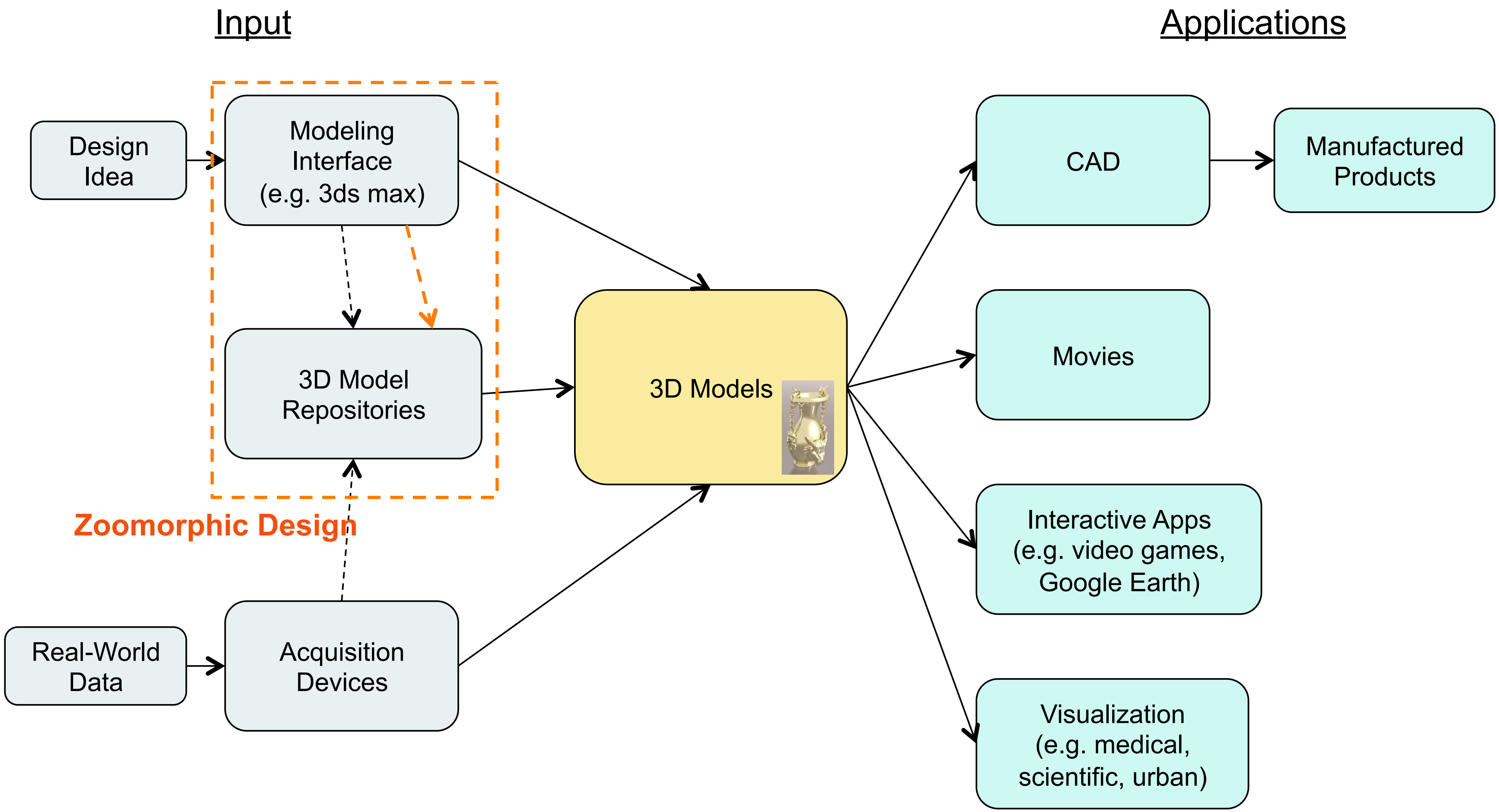
Shape Modeling

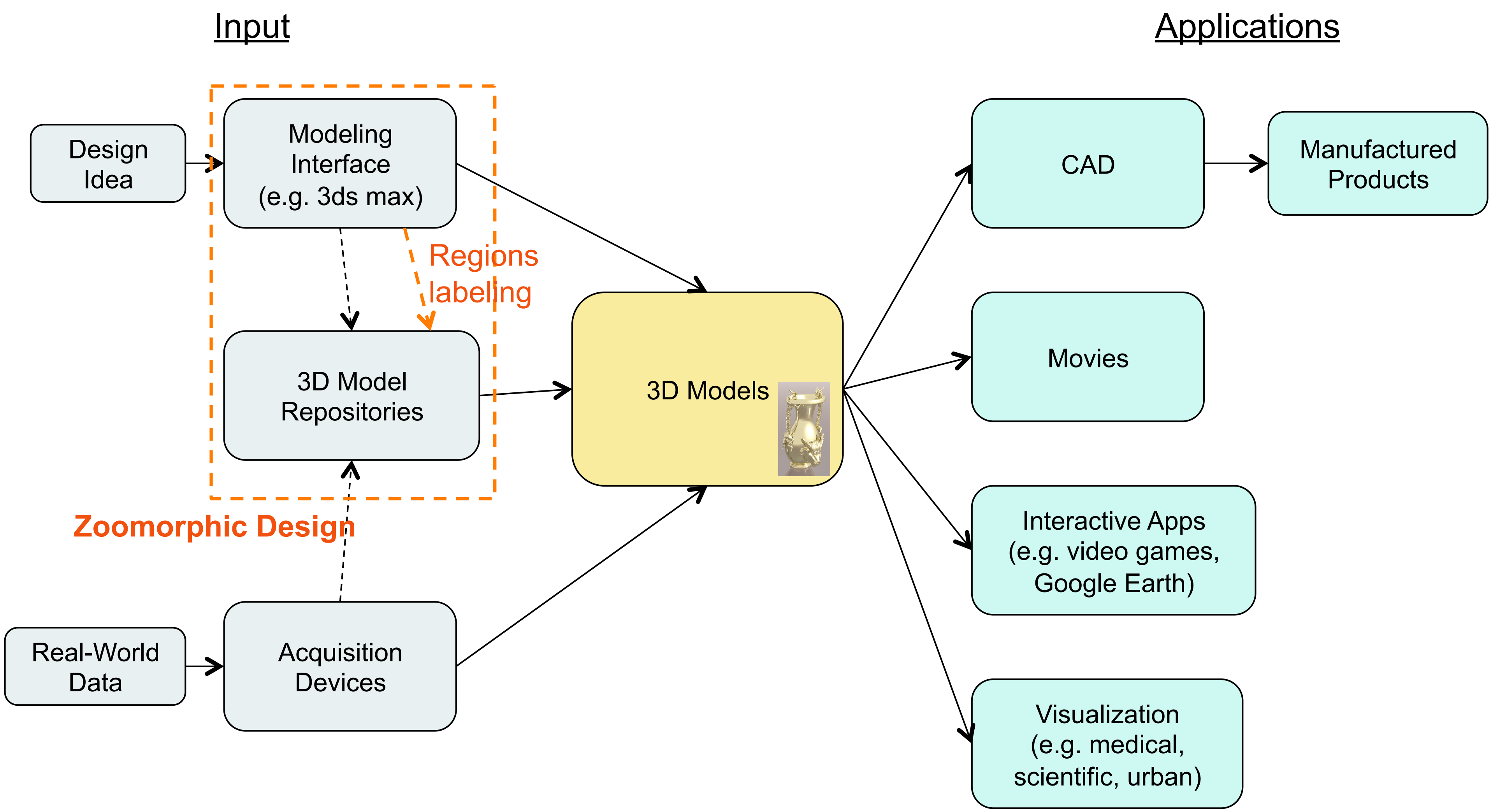
“Zoomorphic Design”, *ACM SIGGRAPH 2015*
Noah Duncan, Lap-Fai Yu, Sai-Kit Yeung, Demetri Terzopoulos



The Big Picture: Zoomorphic Design



The Big Picture: Zoomorphic Design



Motivation

Motivation

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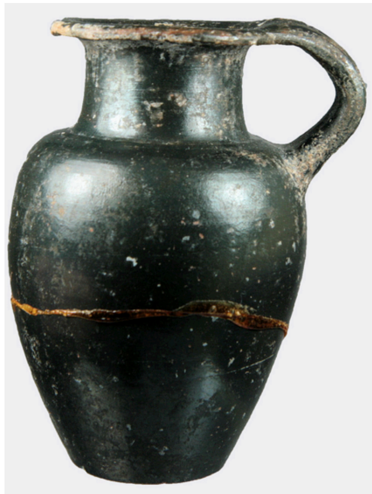

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Motivation

Video

Zoomorphic Design

Noah Duncan[1,3], Lap-Fai (Craig) Yu[2], Sai-Kit Yeung[3], Demetri Terzopoulos[1]

[1]University of California, Los Angeles
[2]University of Massachusetts Boston
[3]Singapore University of Technology and Design

Zoomorphic Design: Summary

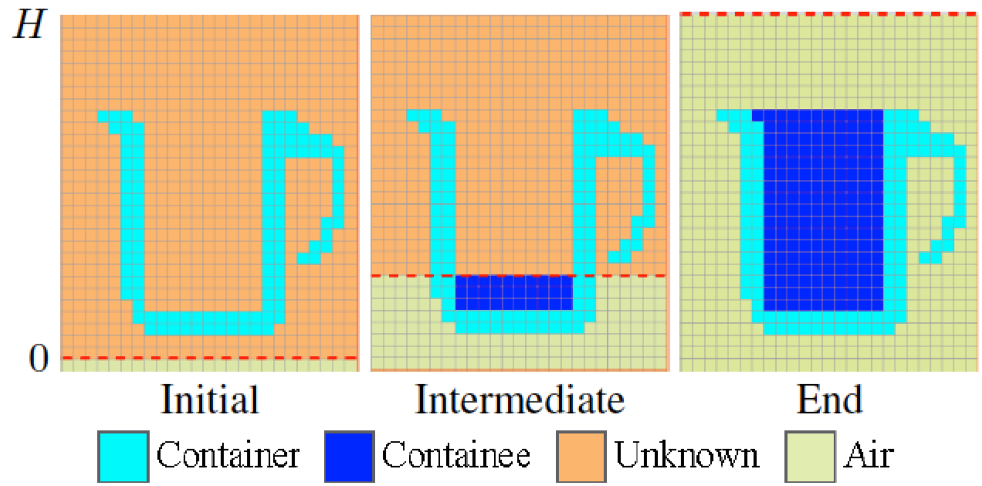
Novelty

- Introduce the problem of zoomorphic shape creation in computer graphics
- First computational approach for zoomorphic shape creation
- Novel design concept Volumetric design restriction (VDR) to ensure functionality

Zoomorphic Design: Summary

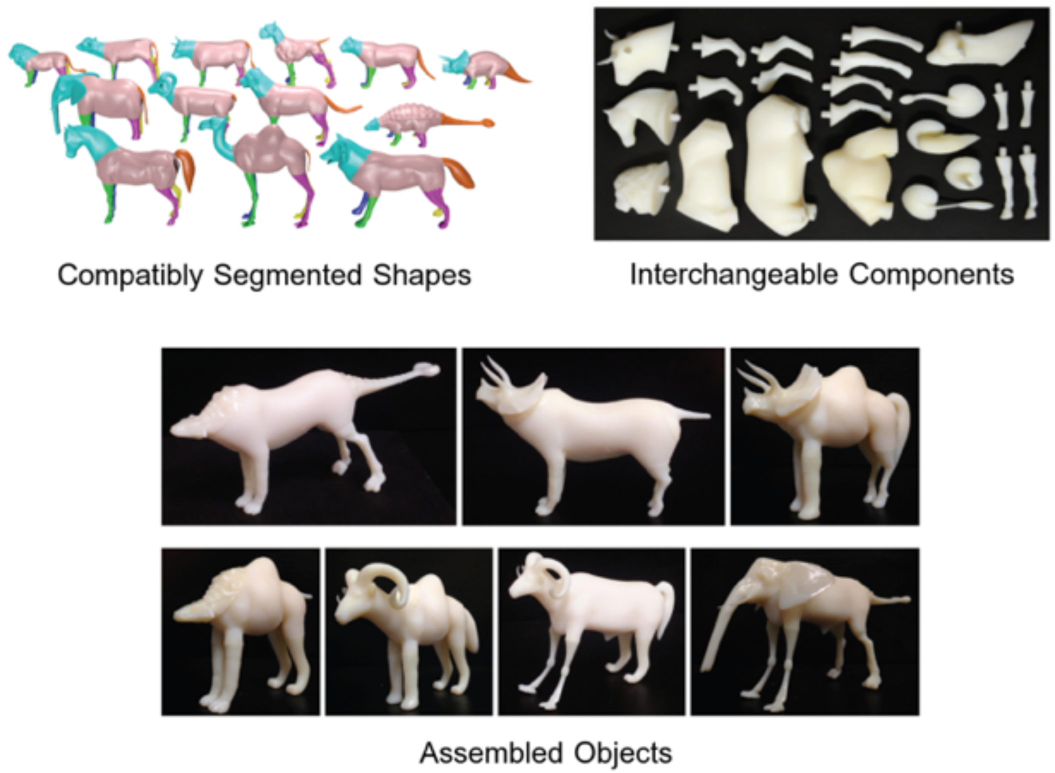
Related project

- Lap-Fai Yu, Noah Duncan, Sai-Kit Yeung. Fill and Transfer: A Simple Physics-based Approach for Containability Reasoning – ICCV 2015



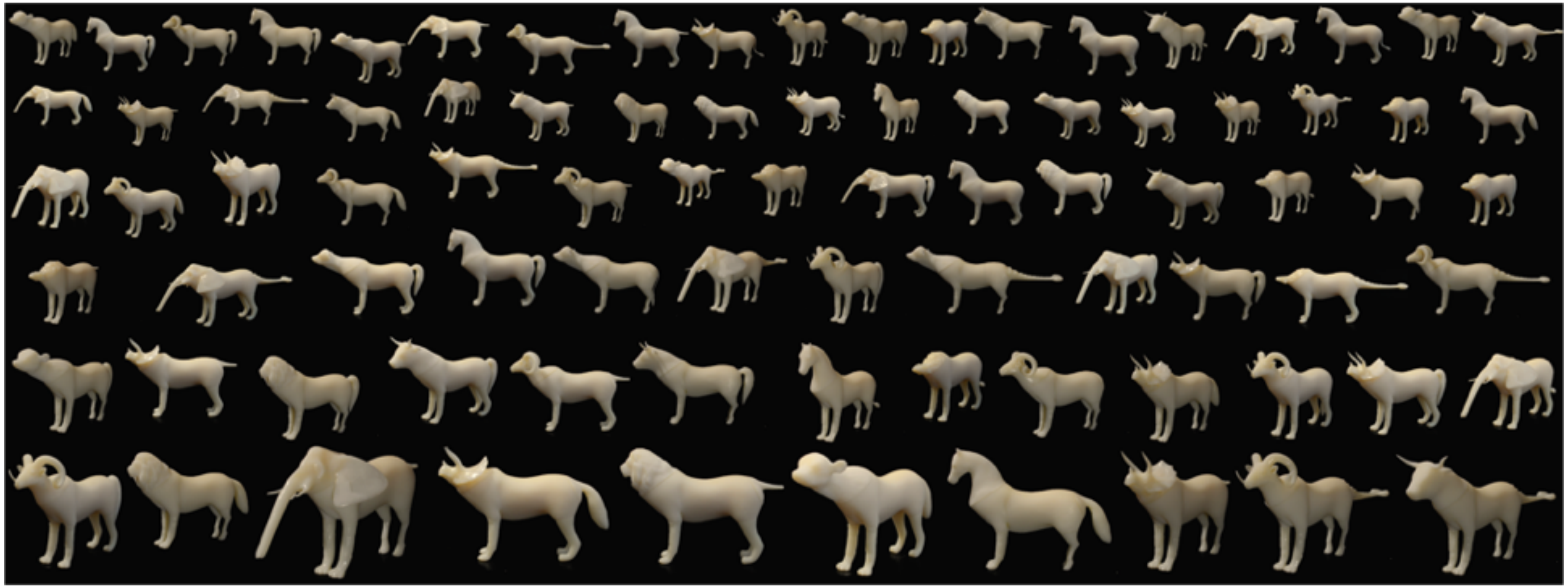
Shape Modeling

- Interchangeable Seamless Components from 3D Models. SIGGRAPHAsia 2016



Shape Modeling

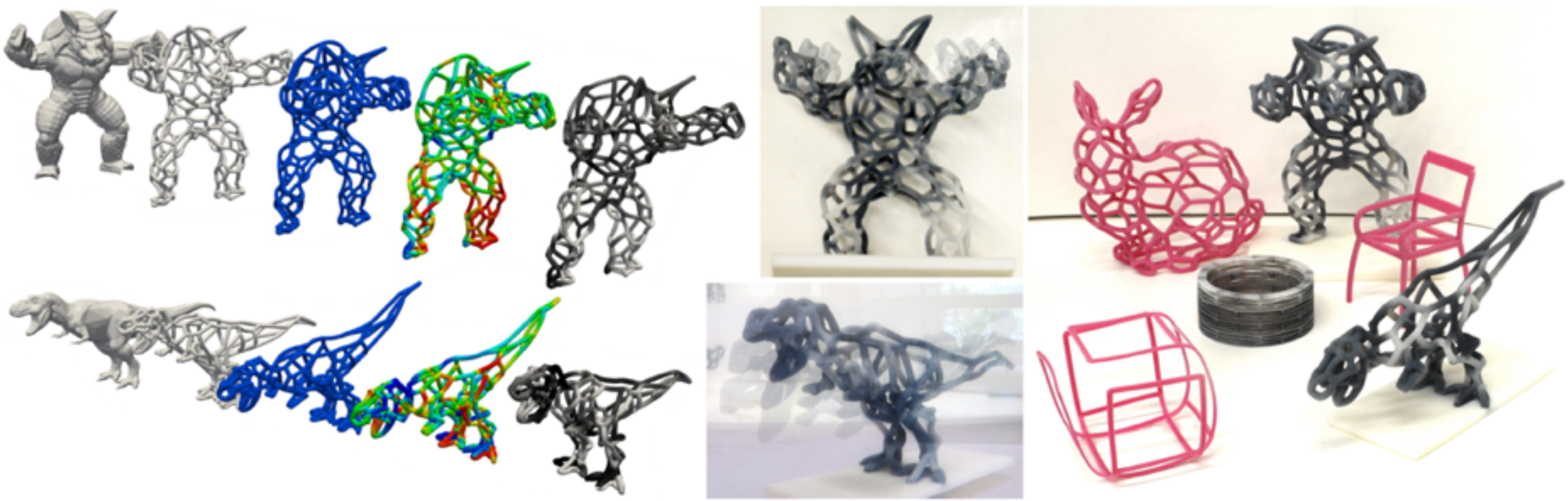
- Interchangeable Seamless Components from 3D Models. SIGGRAPHAsia 2016



Shape Modeling

Computational Fabrication

- Multi-Material Optimization for 4D Printing of Active Rod Structure
  - Oliver Weeger, Benjamin Yue-Sheng Kang, Sai-Kit Yeung, Martin L. Dunn



Outline

Introduction

Motivation

Research showcases

Conclusion

Conclusion

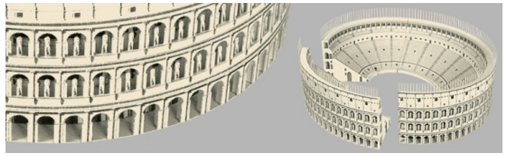
Demonstrated data-driven approaches to:

- ✓ Generate realistic 3D models automatically
- ✓ Facilitate modeling tasks by human users

Conclusion

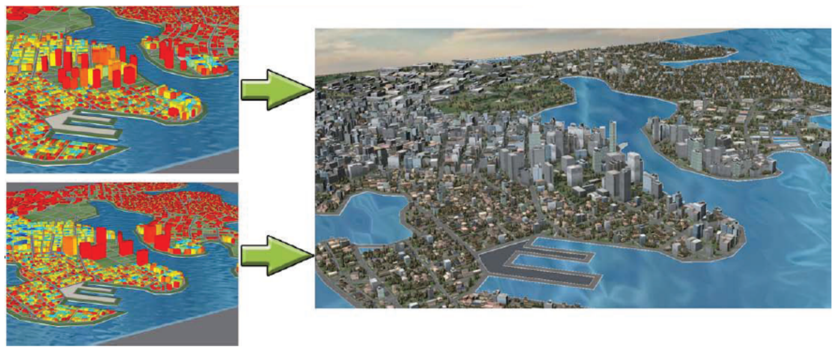
1) Modeling is not privilege of design experts
   - at least, the bottleneck shouldn't be the tools
   - this will open up lots of application opportunities
2) Computer graphics is *not only* about generating nice-looking pictures / computer games
   - though it can be a good motivation ☺
   - modeling is a fundamental step to realism / functionality

Conclusion

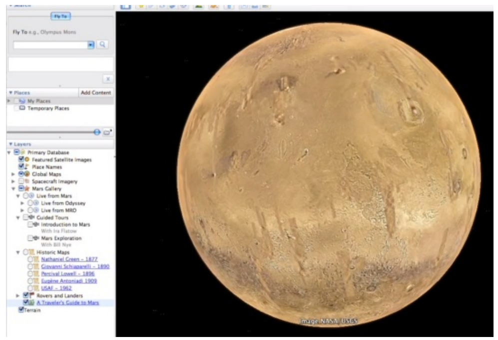


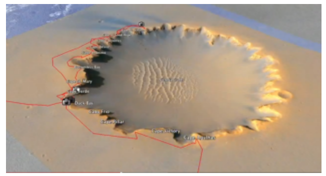
3) Modeling research is highly cross-disciplinary

- scene understanding / analysis, reflectance analysis
  (vision, cognitive science, physics)
- layout generation (ergonomics, aesthetics, robotics)
- 3D reconstruction / visualization
  (urban planning, geography, digital heritage, astronomy)



[Vanegas et al. 2012]





Google Earth / Mars

Future Directions

Real-world data for devising modeling tools

- "best" source of data for realistic scene modeling?
- scene / object understanding
- human priors / physics

[Grabner et al. 2011]

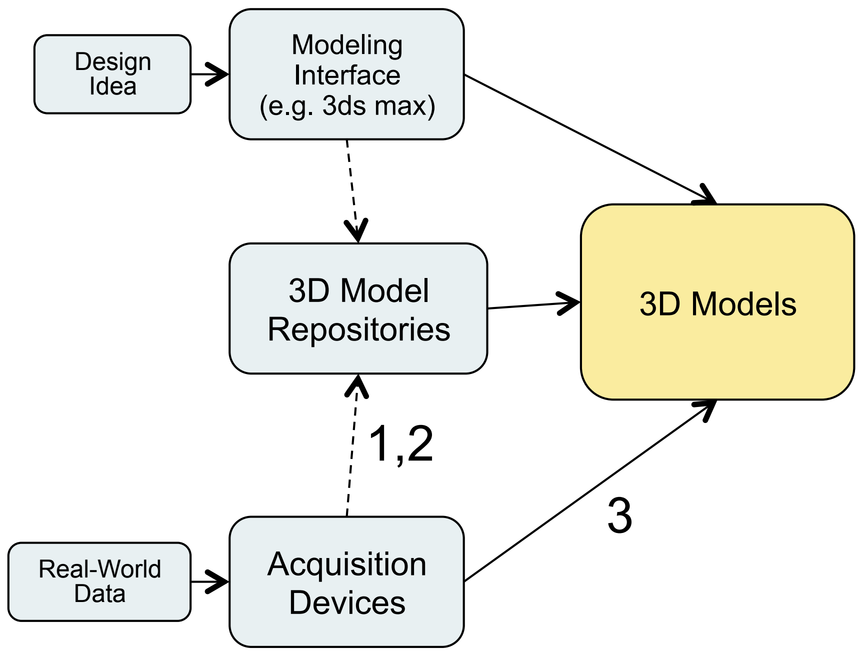
Functional considerations

- human ergonomics in layouts, smart home
- "functional" models

[Zhu et al. 2012]

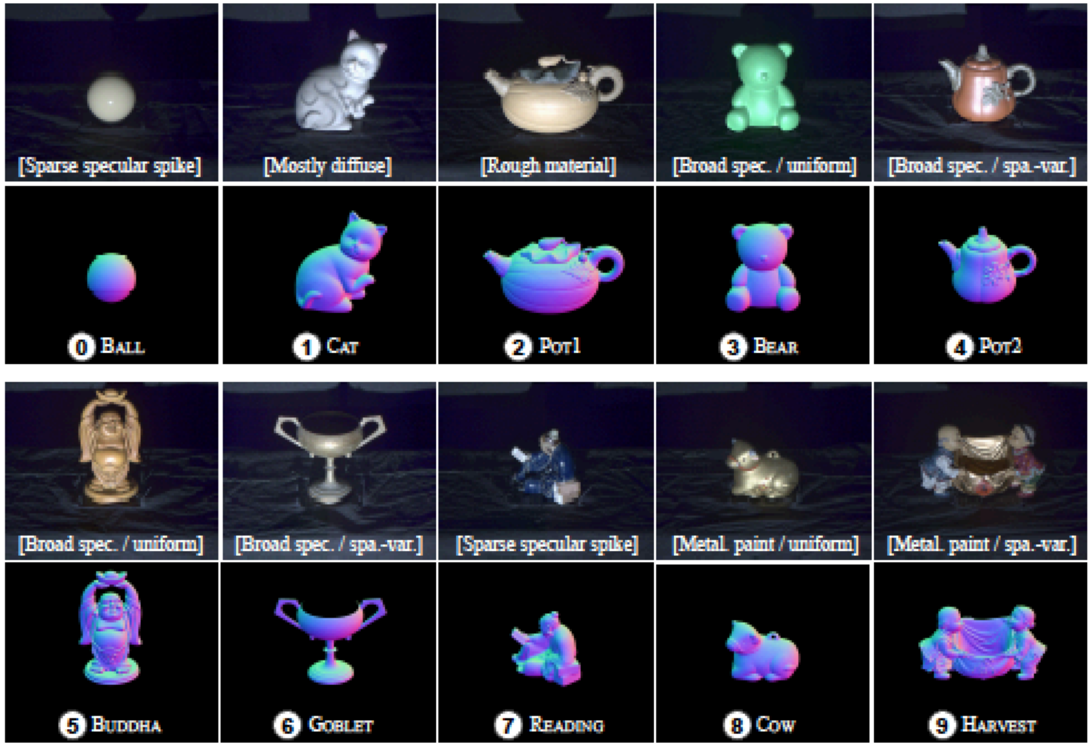
Ongoing topics

1) Photometric Stereo Benchmark dataset
2) RGBD Scene-mesh dataset
3) Reliable wide-baseline matching



Photometric Stereo Benchmark Dataset

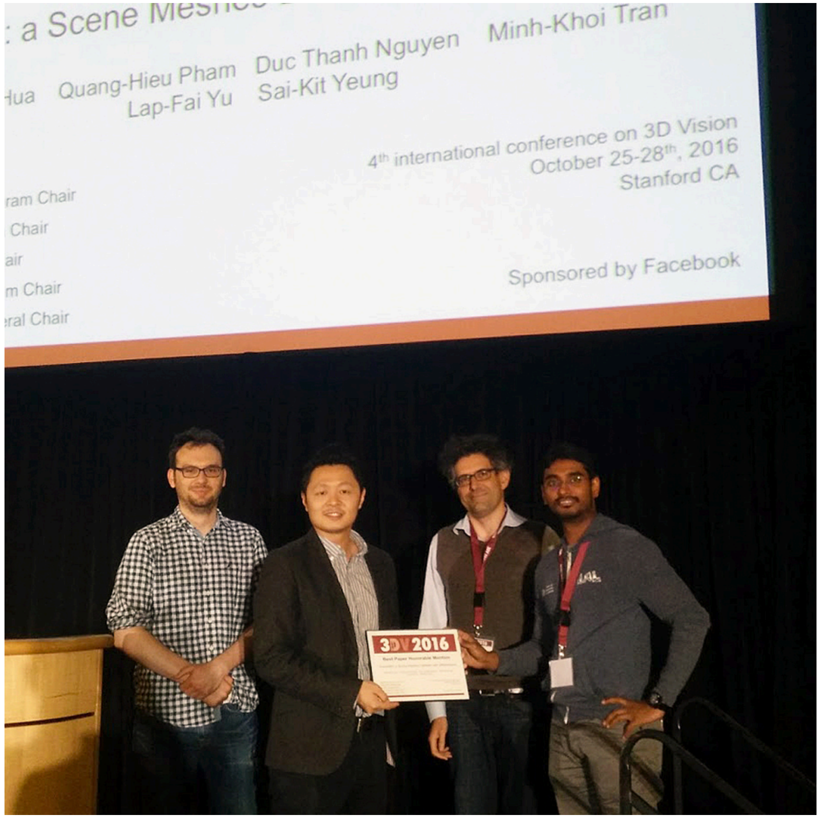
- First of this kind in the computer vision community
- Accepted to IEEE CVPR 2016



A Benchmark Dataset and Evaluation for Non-Lambertian and Uncalibrated Photometric Stereo. IEEE CVPR 2016

Computer Vision

- Object and Scene Understanding
  - SceneNN Dataset



SceneNN: a Scene Meshes Dataset with aNNotations.
Binh-Son Hua, Quang-Hieu Pham,, Duc Thanh Nguyen, Minh-Khoi Tran, Lap-Fai Yu, **Sai-Kit Yeung**
International Conference on 3D Vision (3DV 2016).
Best Paper Honorable Mension

For structure-from-motion

- Good for SfM as it provides large number of wide-baseline matches and does not match scenes of different places.
- Very good for close up objects where baselines can ``accidentally” become very large.
- Top: Furukawa’s database. Previous techniques only produce partial reconstructions
- Texturing is with the superb software, ’Let there be Color!’ =)
- Code and libraries are available at www.kind-of-works.com