WallPlan: Synthesizing Floorplans by Learning to Generate Wall Graphs

Supplementary Material

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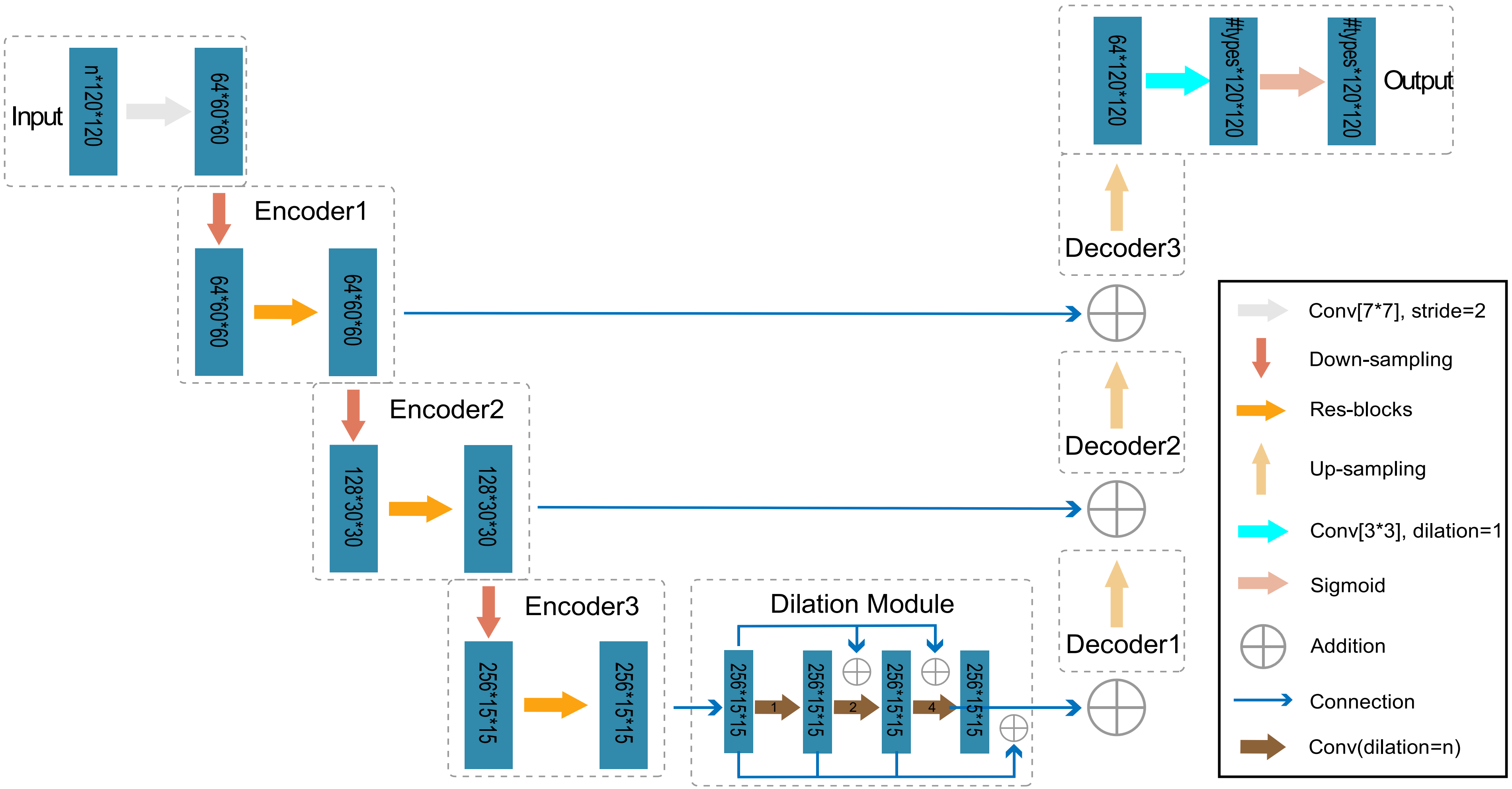
Outline

- Network architecture and training
- Floorplans generated by our method
- Questionnaire for perceptual studies comparison to GT

Modified D-LinkNet [Zhou et al. 2018]



Network architecture

Index	Inputs	Operation	Output Shape
1	-	Multi-channels image	[n,120,120]
2	1	Conv2d(n,64,2)	[64,60,60]
3	2	Batch Normalization	[64,60,60]
4	3	ReLU	[64,60,60]
5	4	Encoder1(3layers)	[64,60,60]
6	5	Encoder2(4layers)	[128,30,30]
7	6	Encoder3(6layers)	[256,15,15]
8	7	Dilation block	[256,15,15]
9	8	Decoder1	[128,30,30]
10	9,6	Decoder2	[64,60,60]
11	10,5	Decoder3	[64,120,120]
12	11	Conv2d(64,#types,1)	[#types,120,120]
13	12	Sigmoid	[#types,120,120]

Encoder module

Module	Index	Inputs	Operation	Output Shape
Input	1	-	Feature map	[64,60,60]
Encoder1	2	-	ResnetBlock(64,64,1)	[64,60,60]
	3	1	ResnetBlock(64,64,1)	[64,60,60]
	4	2	ResnetBlock(64,64,1)	[64,60,60]
Encoder2	5	3	ResnetBlock(64,128,2)	[128,30,30]
	6	4	ResnetBlock(128,128,1)	[128,30,30]
	7	5	ResnetBlock(128,128,1)	[128,30,30]
	8	6	ResnetBlock(128,128,1)	[128,30,30]
Encoder3	9	7	ResnetBlock(128,256,2)	[256,15,15]
	10	8	ResnetBlock(256,256,1)	[256,15,15]
	11	9	ResnetBlock(256,256,1)	[256,15,15]
	12	10	ResnetBlock(256,256,1)	[256,15,15]
	13	11	ResnetBlock(256,256,1)	[256,15,15]
	13	12	ResnetBlock(256,256,1)	[256,15,15]

Decoder module

Module	Index	Inputs	Operation	Output Shape
Input	1	-	Feature map	[256,15,15]
Decoder1	2	1	Conv2d(256,256//4,1)	[64,15,15]
	3	2	Batch Normalization	[64,15,15]
	4	3	Relu	[64,15,15]
	5	4	Deconv2d(64,64,2)	[64,30,30]
	6	5	Batch Normalization	[64,30,30]
	7	6	Relu	[64,30,30]
	8	7	Conv2d(64,128,1)	[128,30,30]
	9	8	Batch Normalization	[128,30,30]
	10	9	Relu	[128,30,30]
Decoder2	11	10	Conv2d(128,128//4,1)	[32,30,30]
	12	11	Batch Normalization	[32,30,30]
	13	12	Relu	[32,30,30]
	14	13	Deconv2d(32,32,2)	[32,60,60]
	15	14	Batch Normalization	[32,60,61]
	16	15	Relu	[32,60,62]
	17	16	Conv2d(32,64,1)	[64,60,60]
	18	17	Batch Normalization	[64,60,60]
	19	18	Relu	[64,60,60]
Decoder3	20	19	Conv2d(64,64//4,1)	[16,60,60]
	21	20	Batch Normalization	[16,60,61]
	22	21	Relu	[16,60,62]
	23	22	Deconv2d(16,16,2)	[16,120,120]
	24	23	Batch Normalization	[16,120,120]
	25	24	Relu	[16,120,120]
	26	25	Conv2d(16,64,1)	[64,120,120]
	27	26	Batch Normalization	[64,120,120]
	28	27	Relu	[64,120,120]

Dilation module

Index	Inputs	Operation	Output Shape
1	-	Feature map	[256,15,15]
2	1	Conv2d(256,256,1,dilation=1)	[256,15,15]
3	2,0	Conv2d(256,256,1,dilation=2)	[256,15,15]
4	3,0	Conv2d(256,256,1,dilation=4)	[256,15,15]
5	4,3,2,1	Addition	[256,15,15]

Hyper parameters

Hyper parameters	**Value**
Batch size	16
Epoch	60
Optimizer	Adam
Learning rate*	1.2e-4
Weight decay	1e-4

*For all networks, we adopt a “poly” learning rate policy: the learning rate is multiplied by $(1 - \frac{current\_epoch}{\max\_epoch})^{power}$ with power = 1.5.

WinNet

To predict the living room window, the input to WinNet is a multi-channel image which default to 0 at each pixel:

- Inside mask: taking a value of 1 for the interior.
- Boundary mask: taking a value of 1 for the exterior walls.
- Entrance mask: taking a value of 1 for the front door.

To predict the windows of other type rooms, the input to WinNet is a multi-channel image which default to 0 at each pixel:

- Inside mask: taking a value of 1 for the interior.
- Boundary mask: taking a value of 1 for the exterior walls.
- Entrance mask: taking a value of 1 for the front door.
- living room mask: taking a value of 1 for the living room window.

WinNet outputs a semantic segmentation of windows, taking a value of 1 for the window and 0 for nothing.

GraphNet

To generate new nodes and edges, the input to GraphNet is a multi-channel image which default to 0 at each pixel:

- Inside mask: taking a value of 1 for the interior.
- Boundary mask: taking a value of 1 for the exterior walls.
- Entrance mask: taking a value of 1 for the front door.
- Window mask: taking a value of 1 for the living room window and 2 for other windows.
- Wall graph mask: taking a value of 1 for edges in the wall graph.
- Source node mask: taking a value of 2 for the source nodes and 1 for other nodes.
- Semantics mask: the floorplan semantics predicted by LabelNet.

GraphNet outputs a semantic segmentation of the new nodes and edge, taking a value of 1 for the new edge and 2 for the new node.

LabelNet

To predict the floorplan semantics, the input to LabelNet is a multi-channel image which default to 0 at each pixel:

- Inside mask: taking a value of 1 for the interior.
- Boundary mask: taking a value of 1 for the exterior walls.
- Entrance mask: taking a value of 1 for the front door.
- Window mask: taking a value of 1 for the living room window and 2 for other windows.
- Wall graph mask: the wall graph generated by GraphNet.

LabelNet outputs a semantic segmentation of room labels, taking a value of 0 for nothing, 1 for the wall, 2 for the living room, 3 for the bedroom, 4 for the kitchen, 5 for the bathroom, 6 for the balcony and 7 for the storage.

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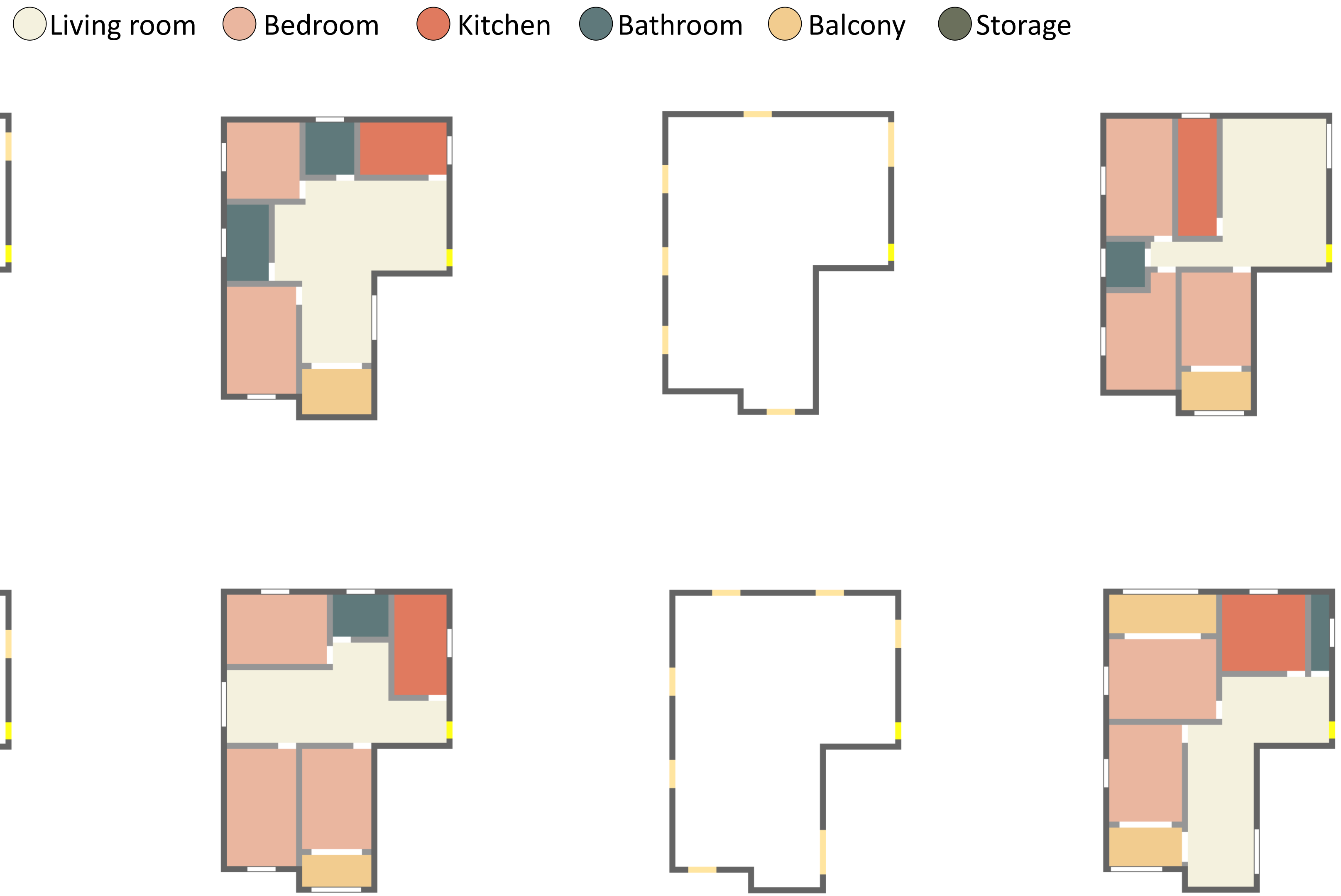
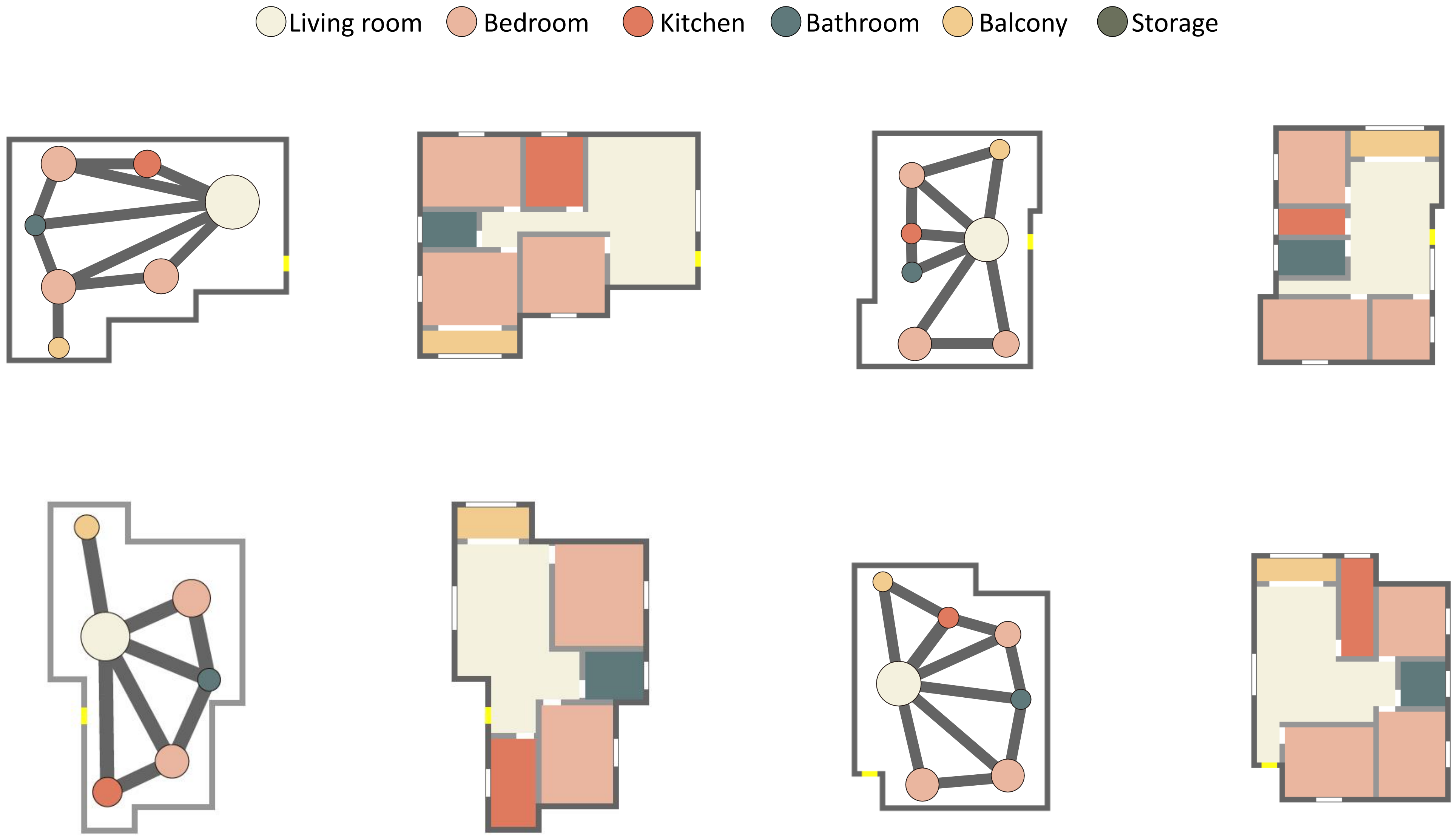
Only boundary

Only boundary

Window constraint

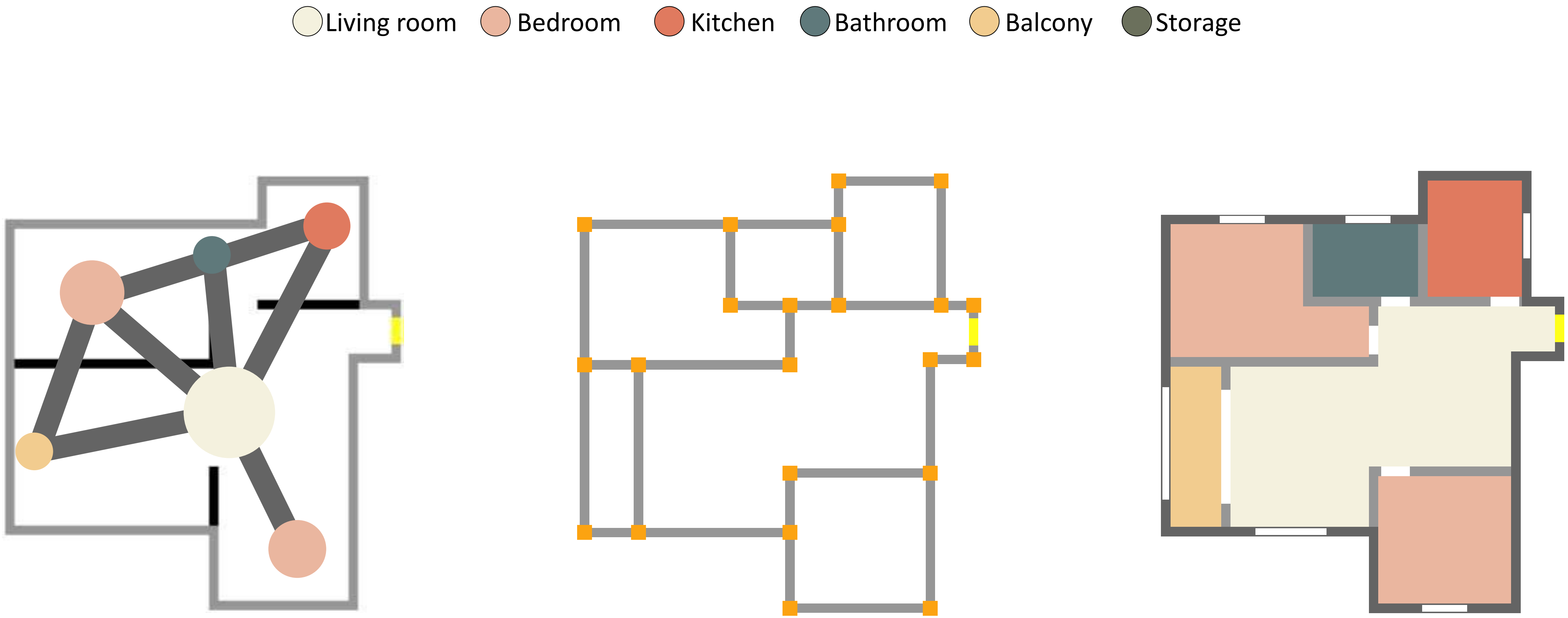


Bubble diagram constraint



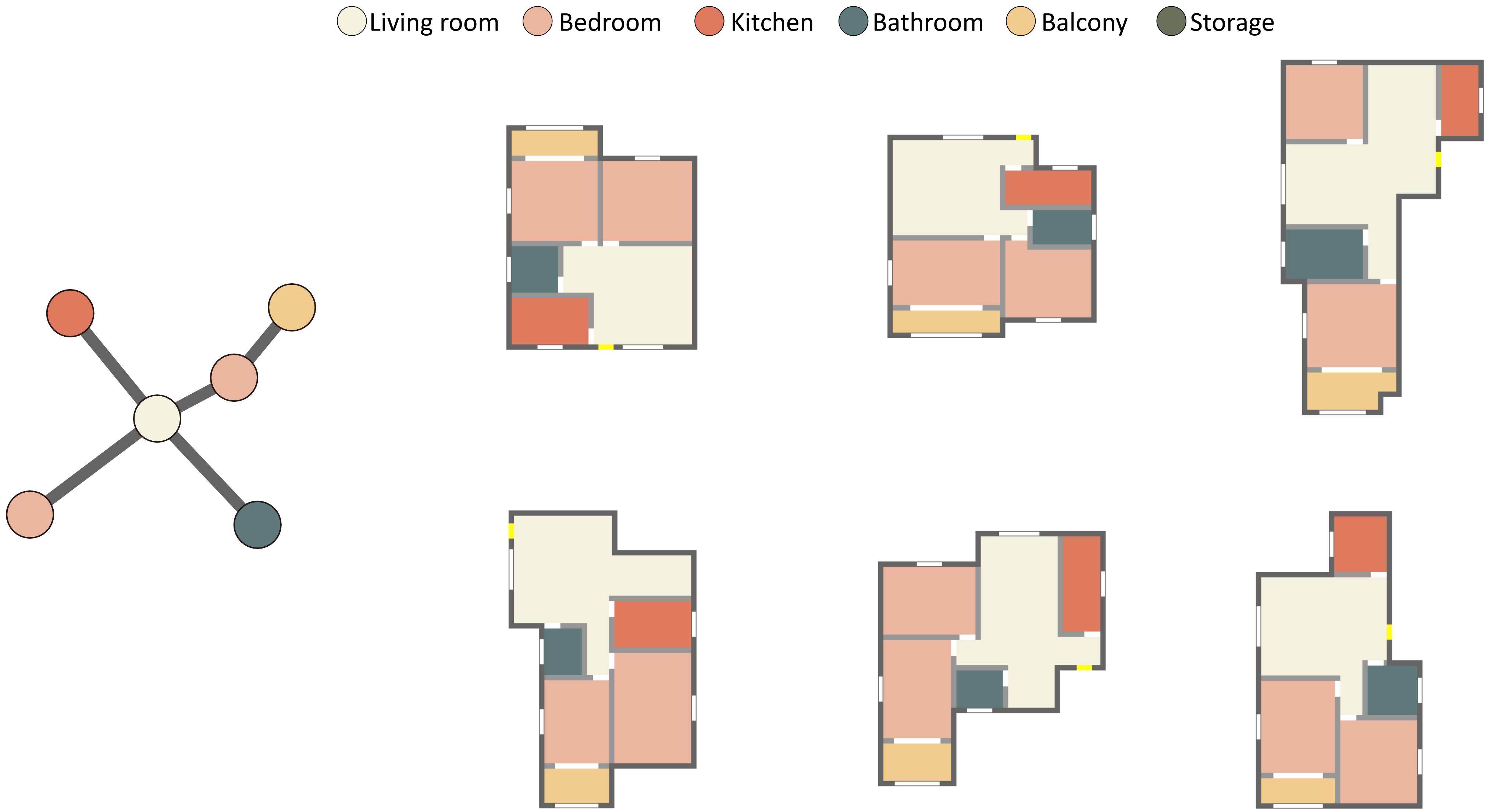
Loading-bearing wall constraint

Hybrid-constraint

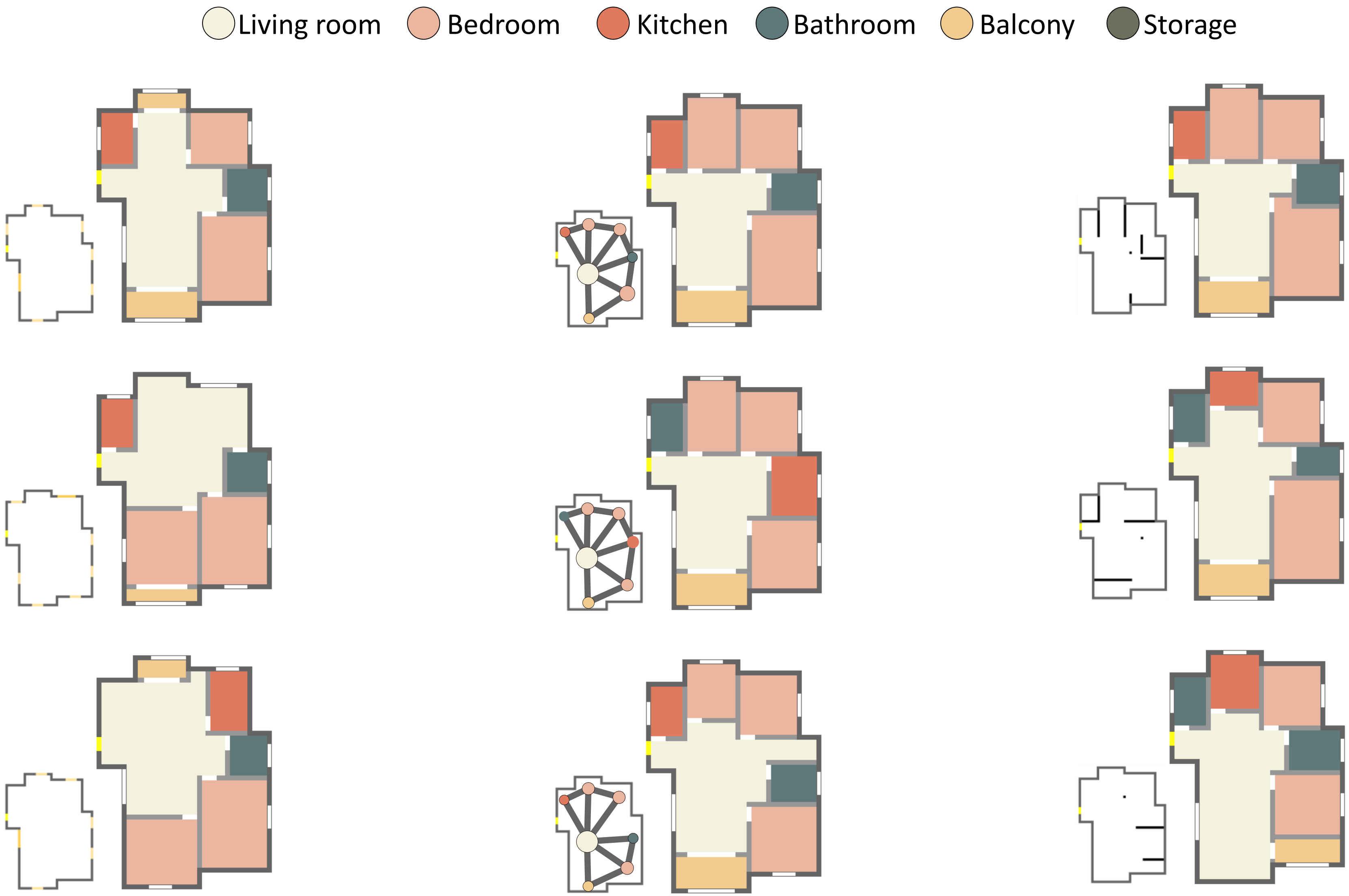


Free generation

Free generation



Multiple floorplans



Nearest neighbors from dataset

Our result | Nearest neighbor 1 | Nearest neighbor 2 | Nearest neighbor 3

Nearest neighbors from dataset

Our result Nearest neighbor 1 Nearest neighbor 2 Nearest neighbor 3

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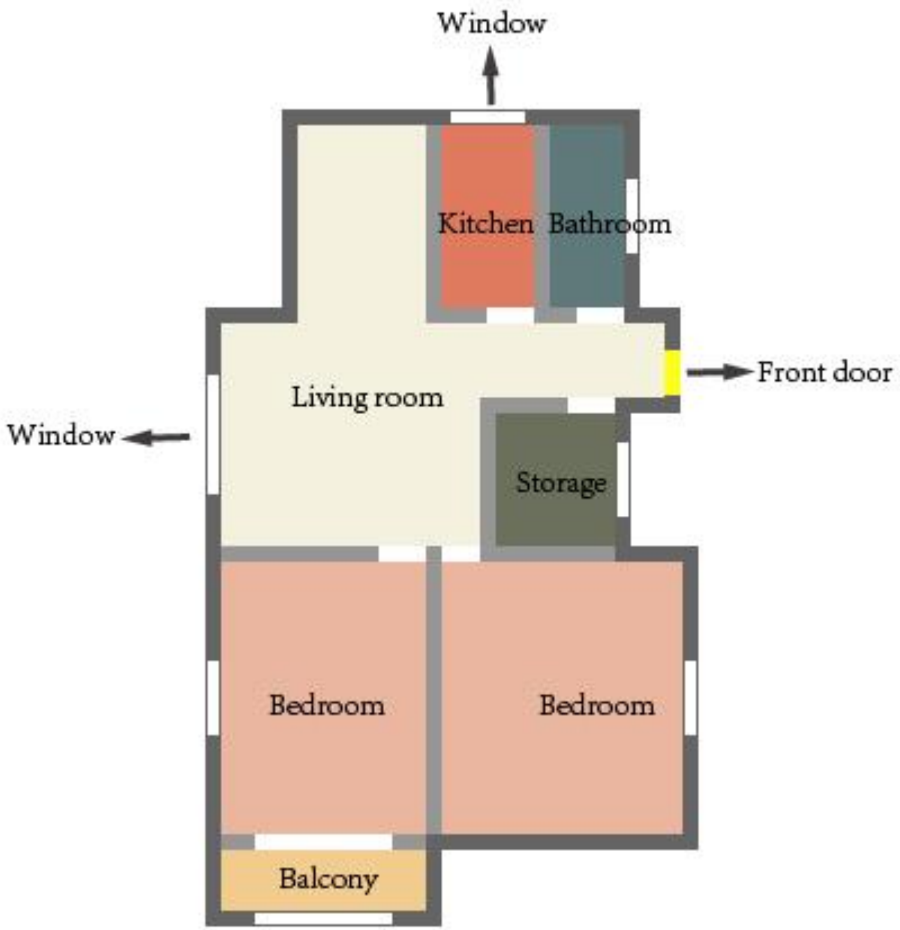
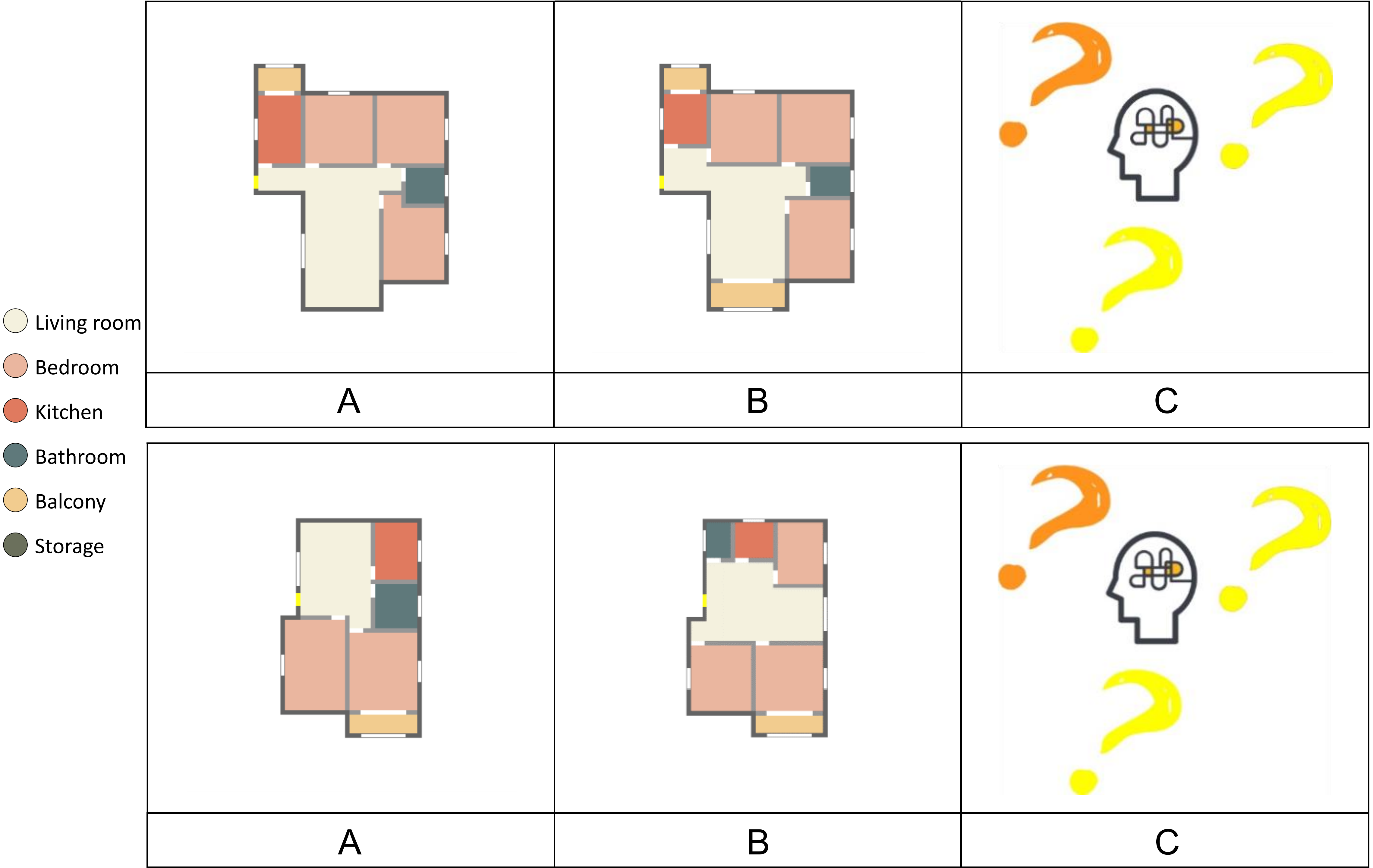
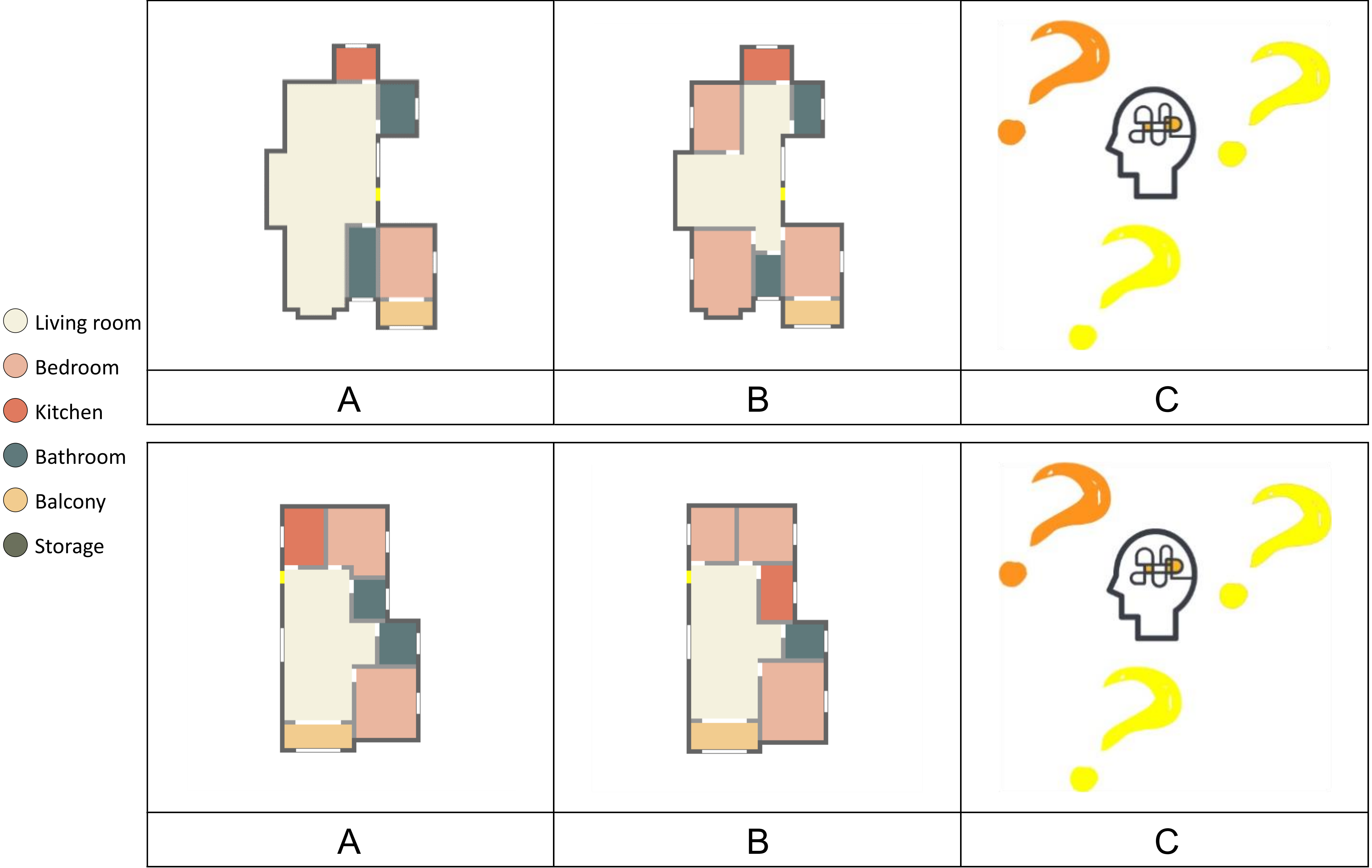
Which one do you think is more plausible in the following floorplans? If it is difficult for you to judge, choose C for “Not sure”.

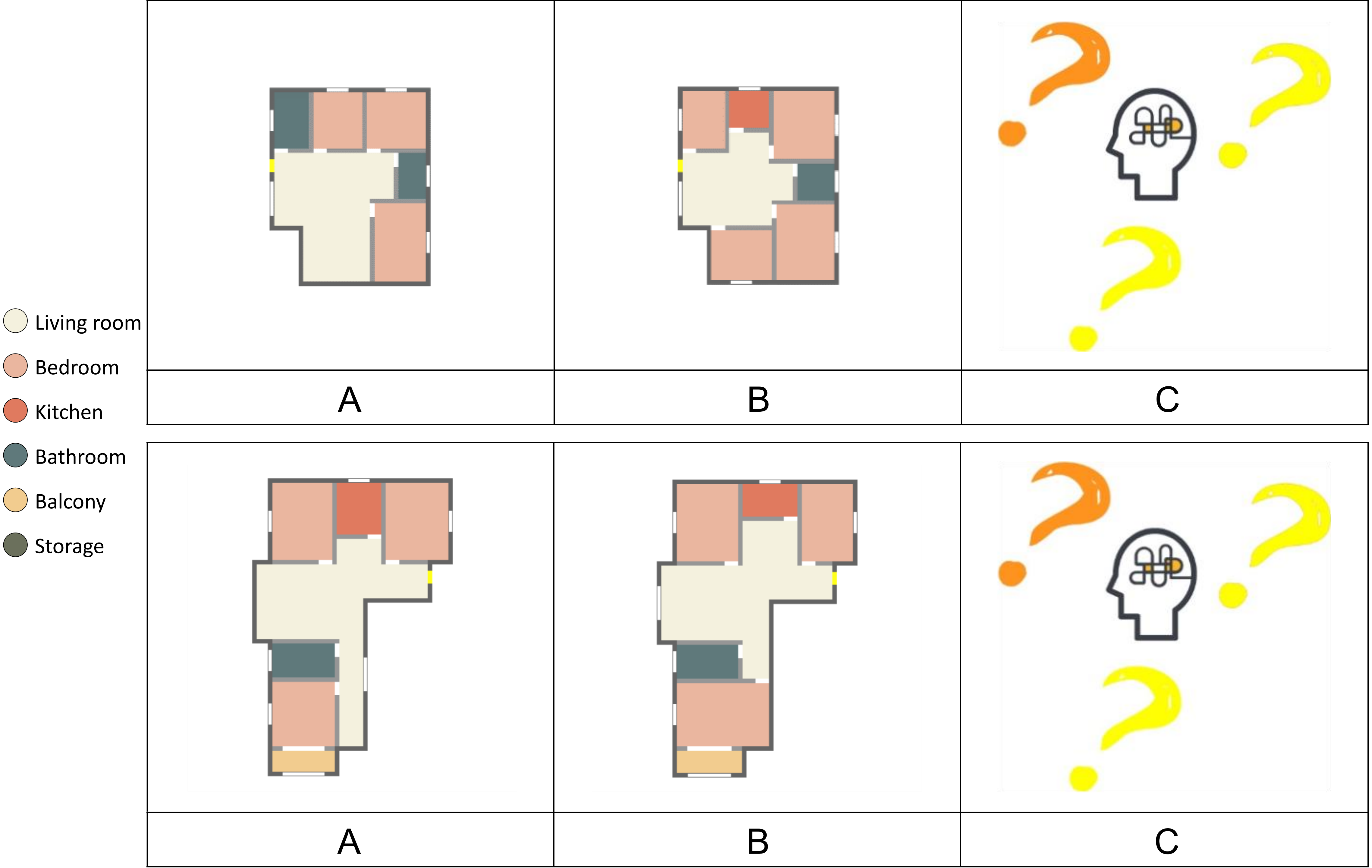


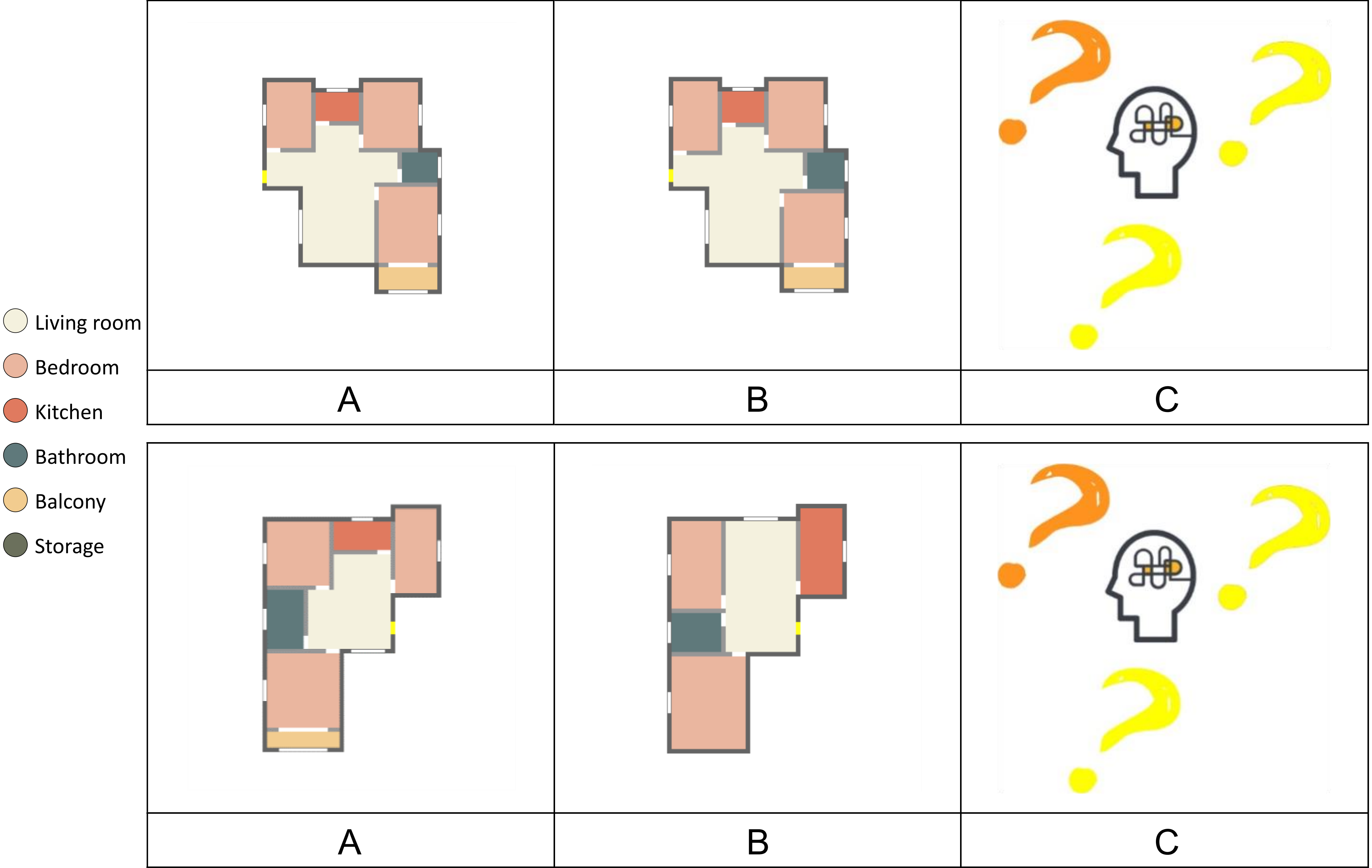
An example floorplan for visualization

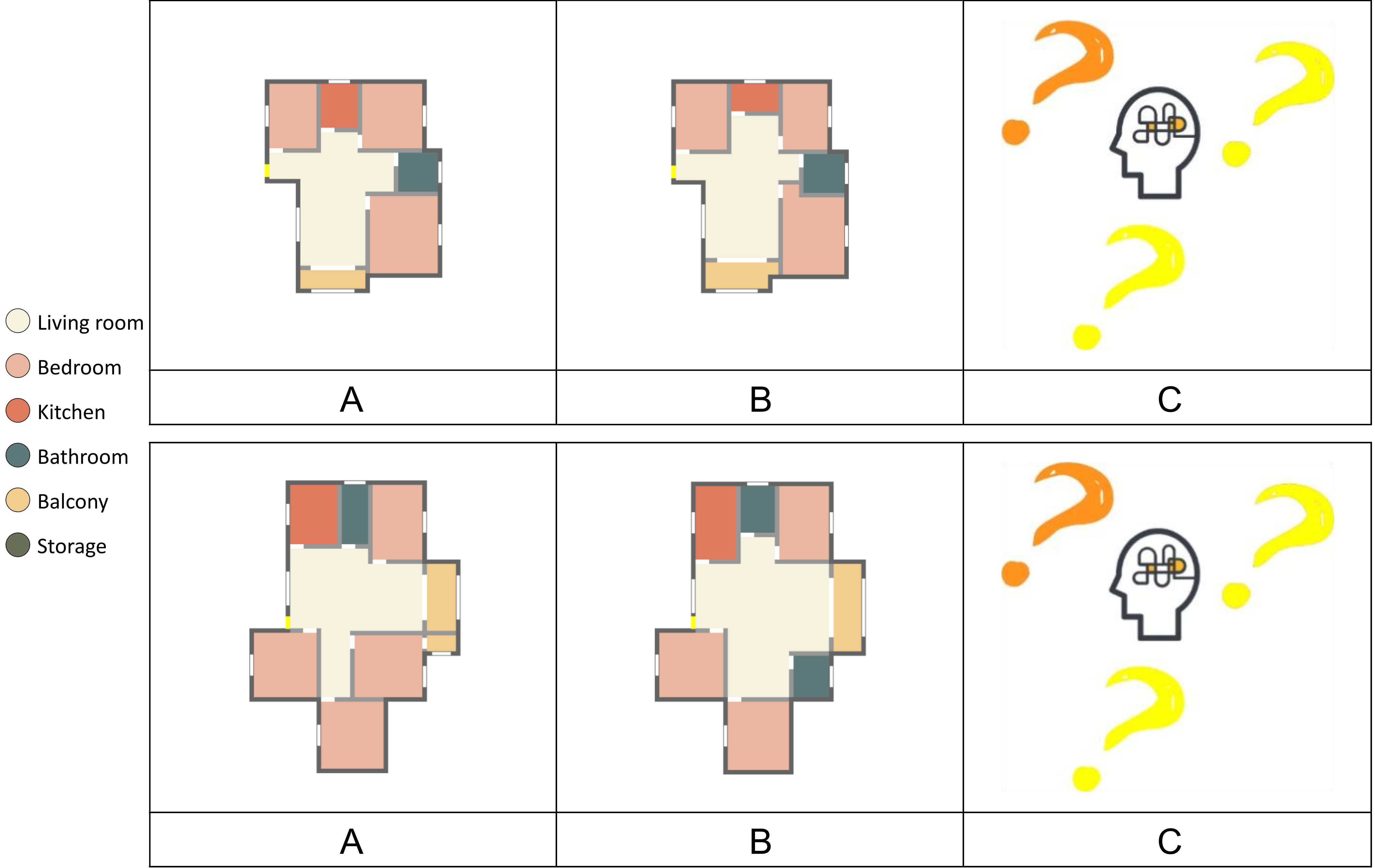

Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C

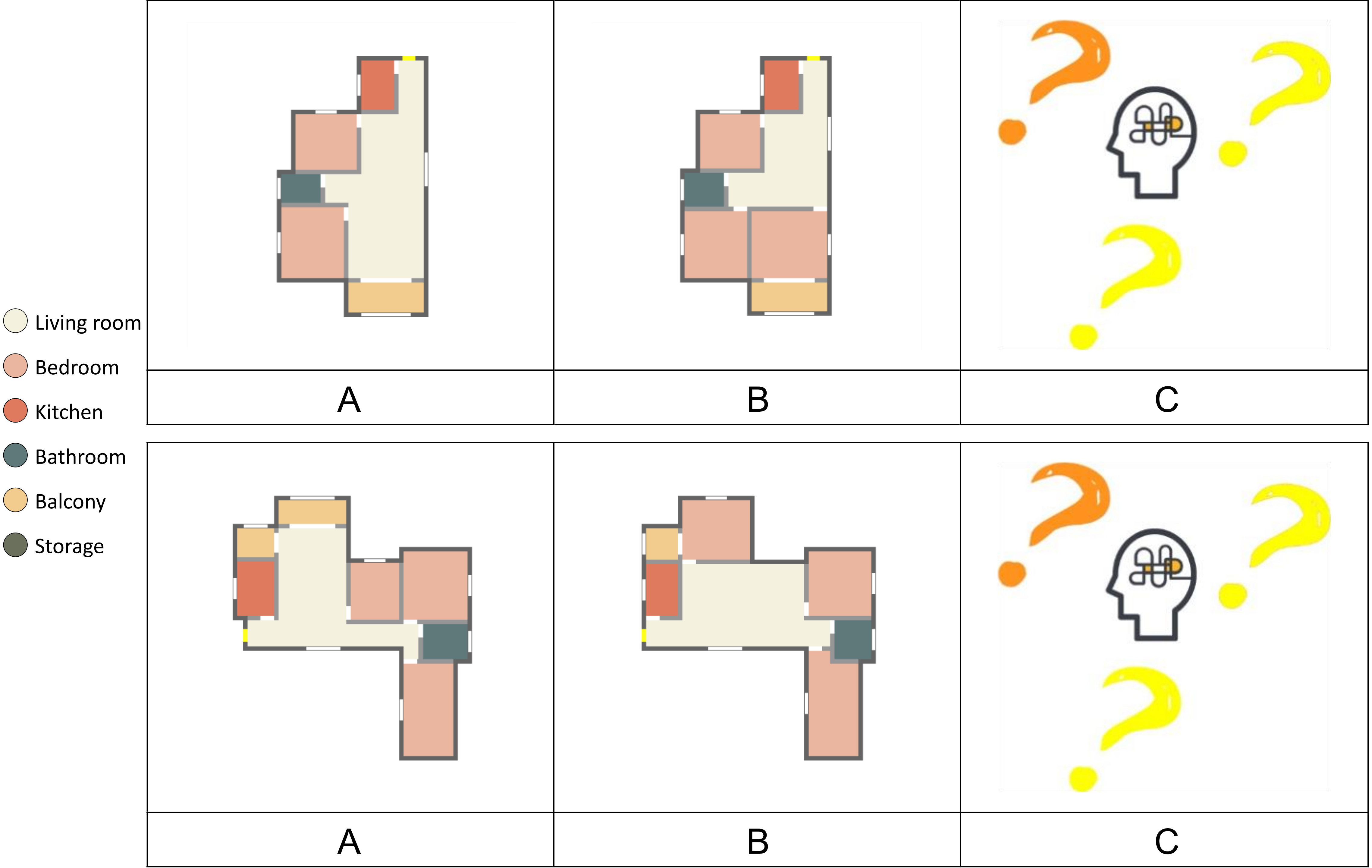


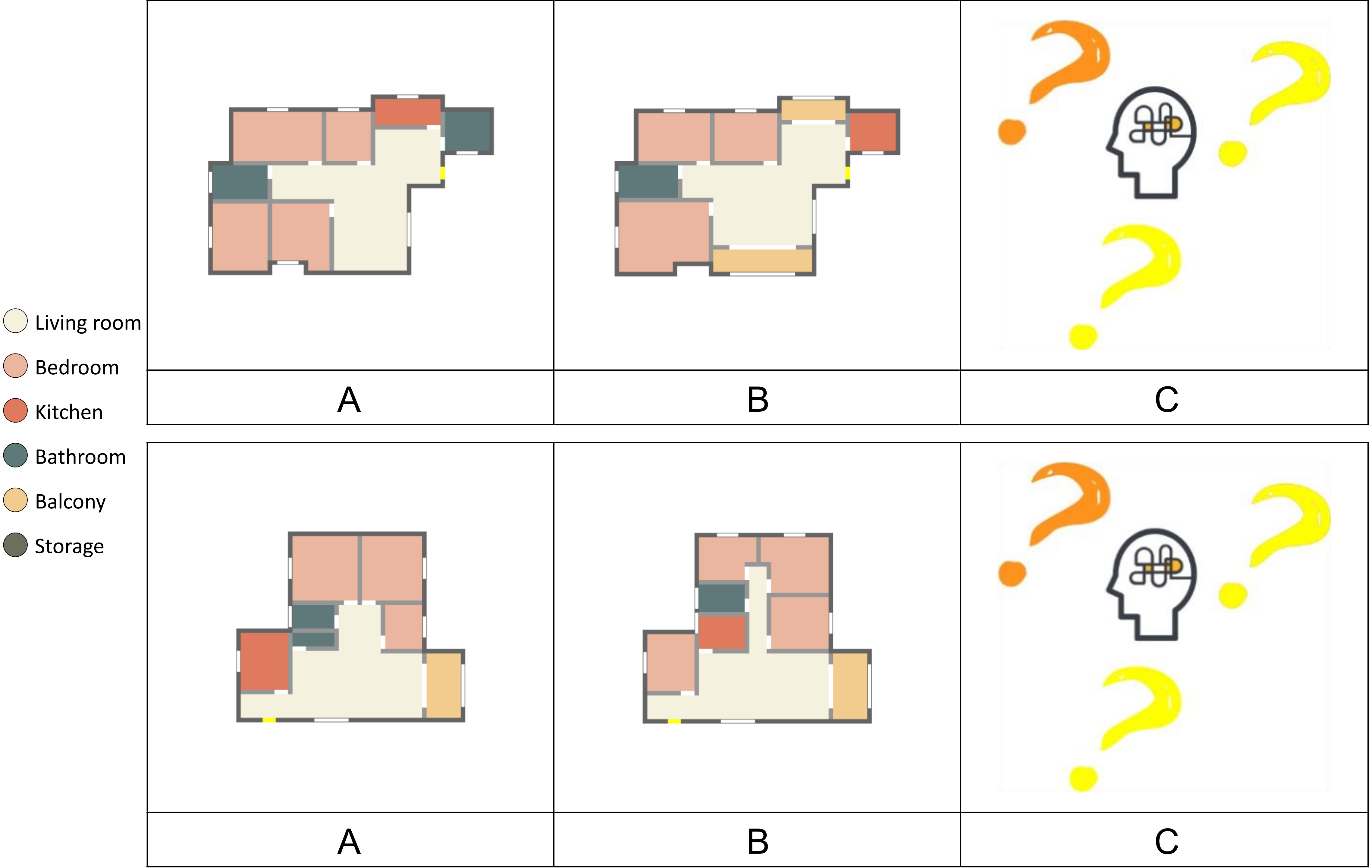
Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C

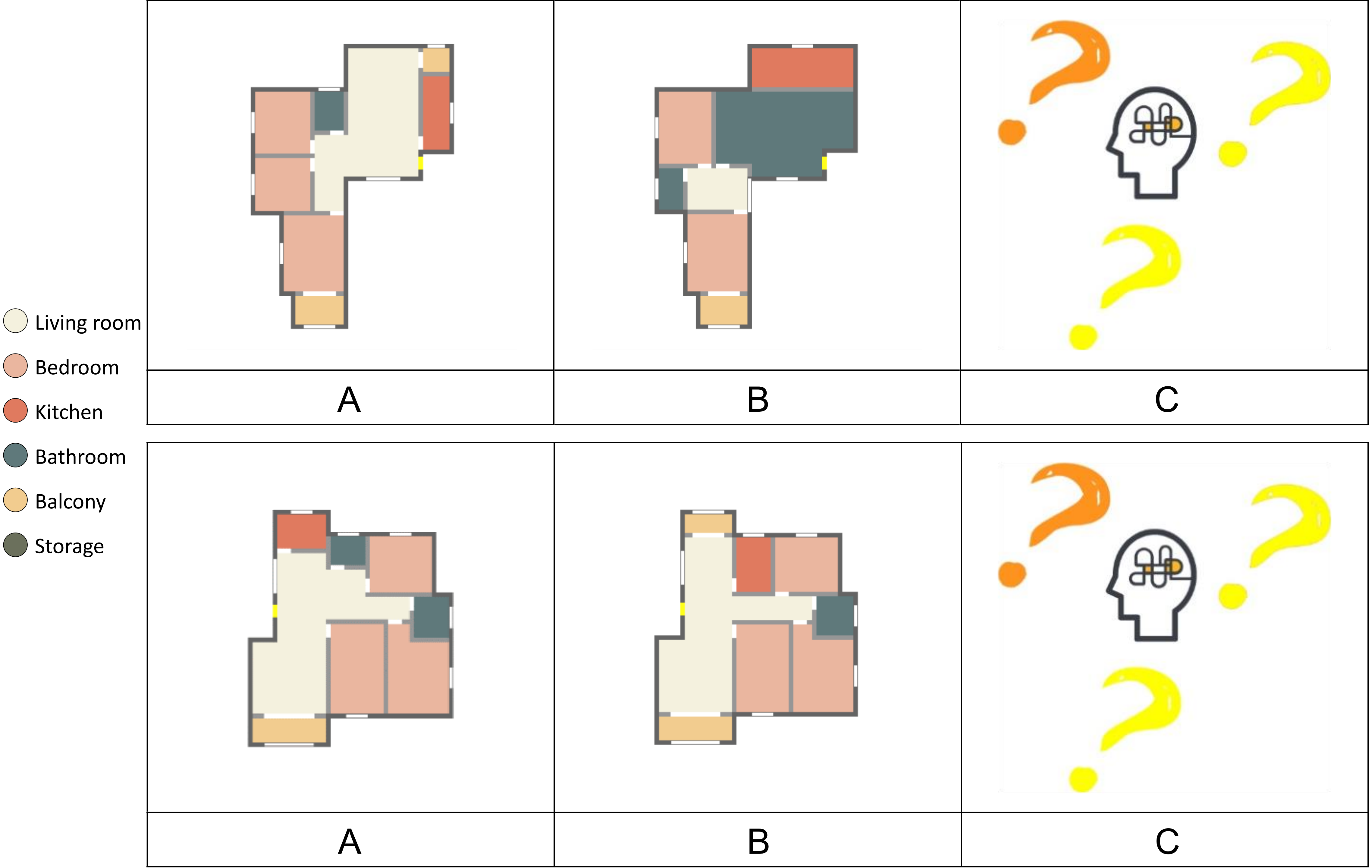

Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C

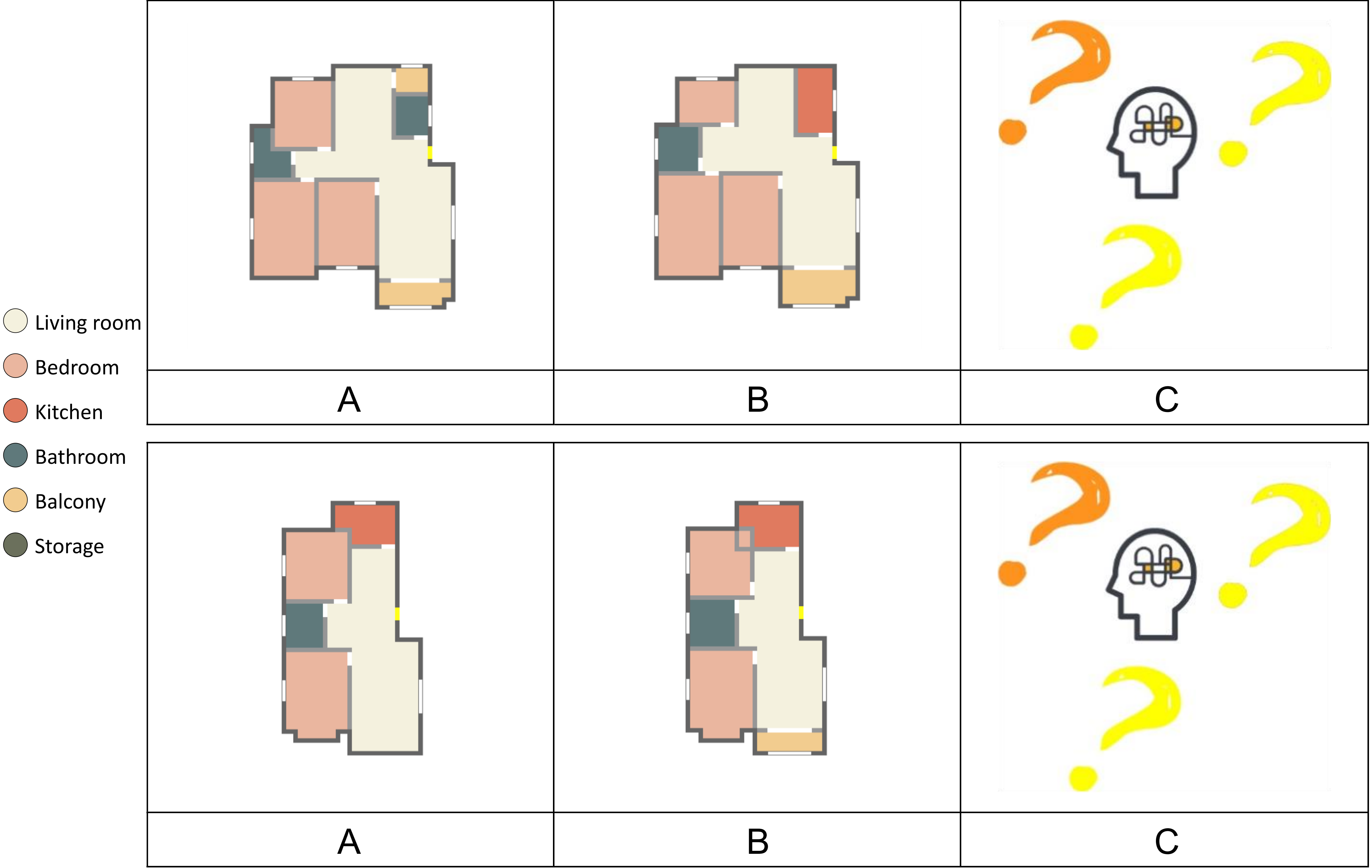

Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C

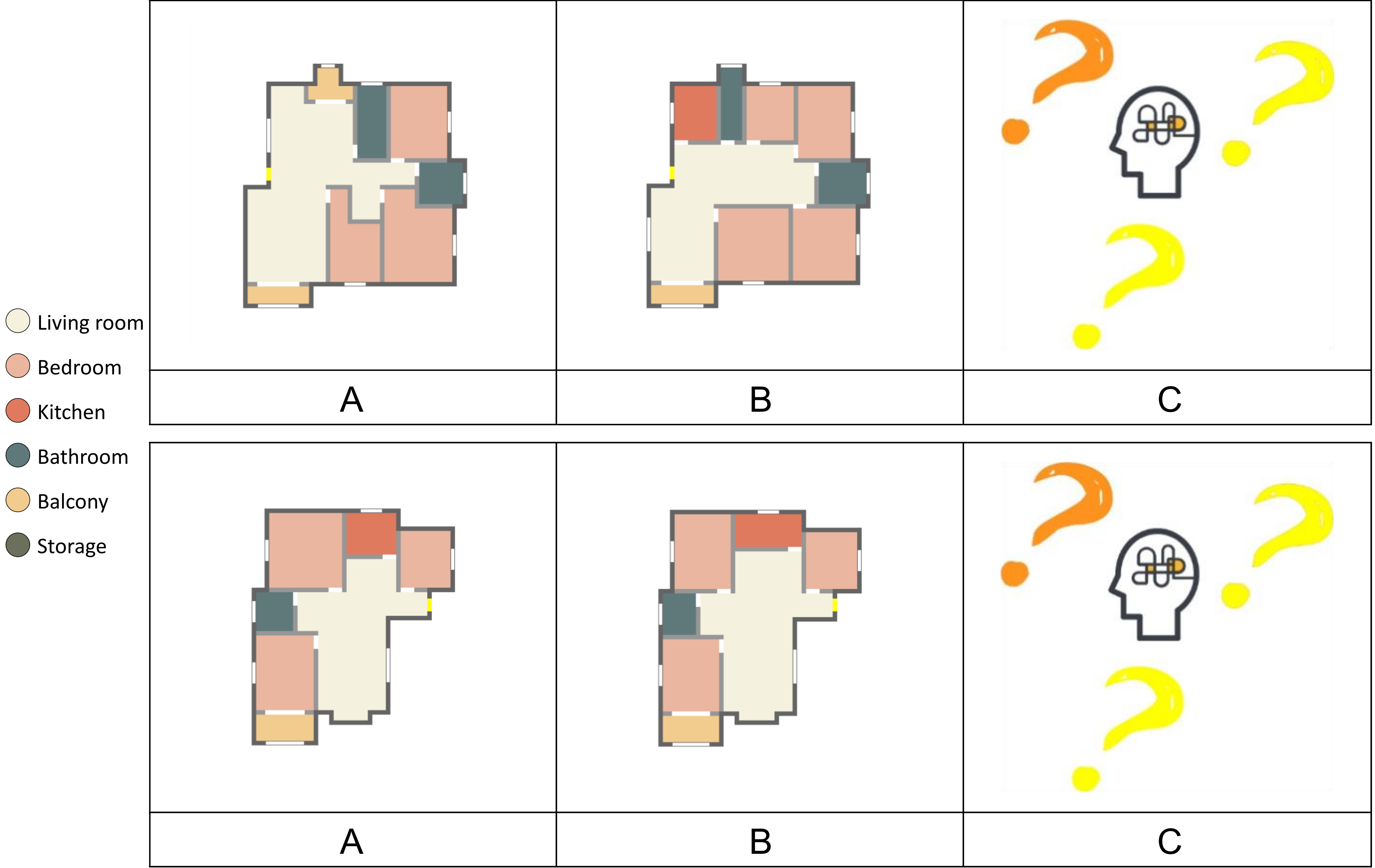

Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C

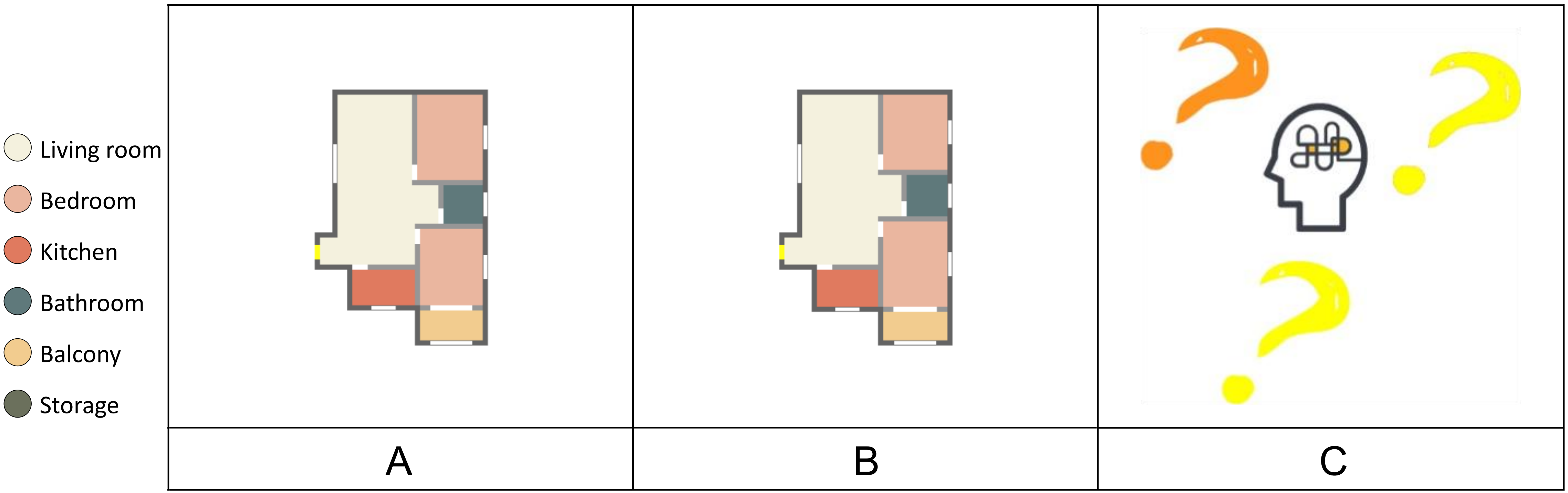

Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C


Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C


Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C


Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C


Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C
A
B
C


Living room
Bedroom
Kitchen
Bathroom
Balcony
Storage
A
B
C

Thank you