Spatial Data Mining: A Deep Dive Into Space-Time Analysis

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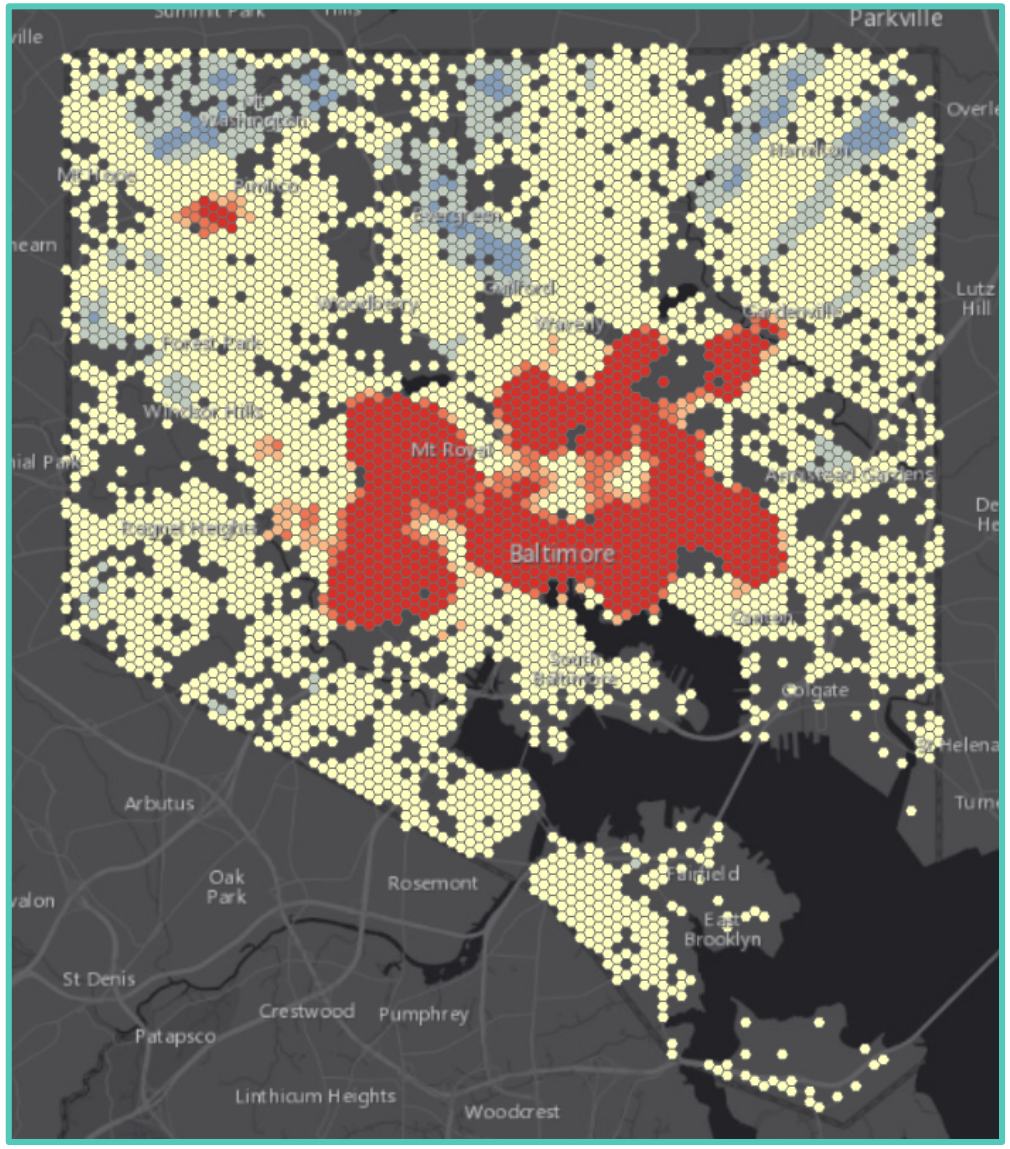
Jenora D'Acosta

Flora Vale

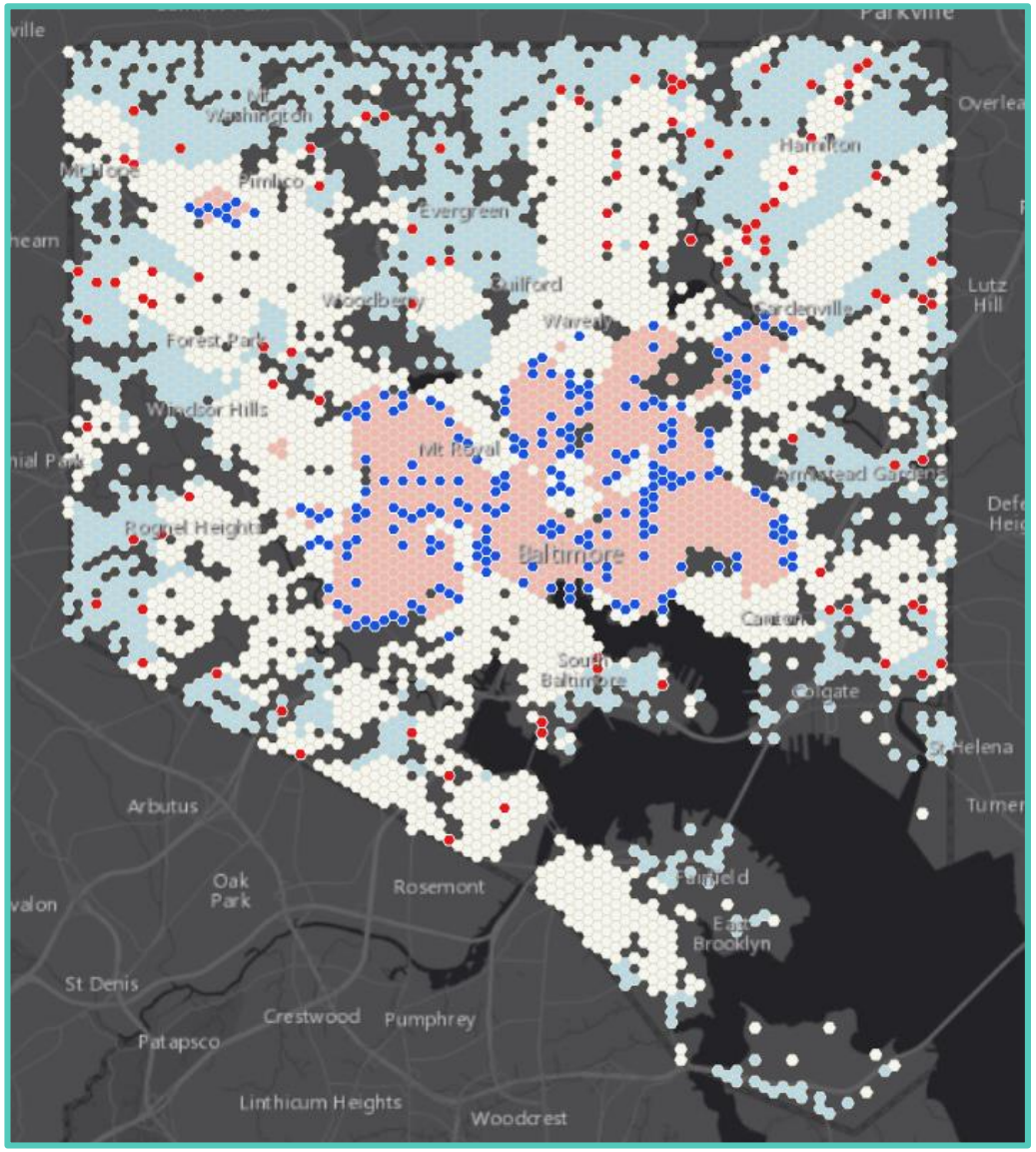
esriurl.com/spatialstats

GIS INSPIRING WHAT'S NEXT

Quantifying Spatial Clusters

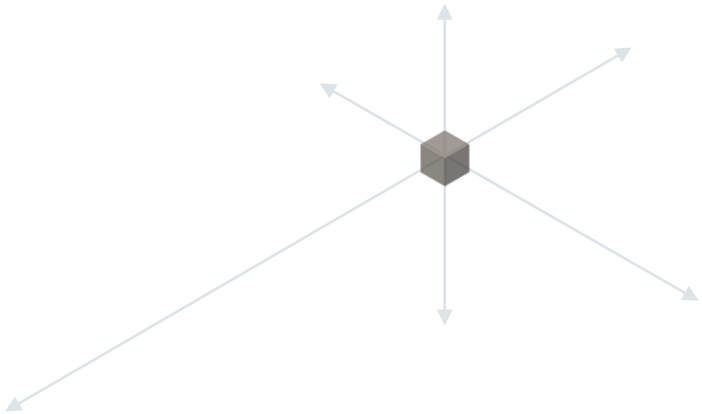


Hot Spot Analysis



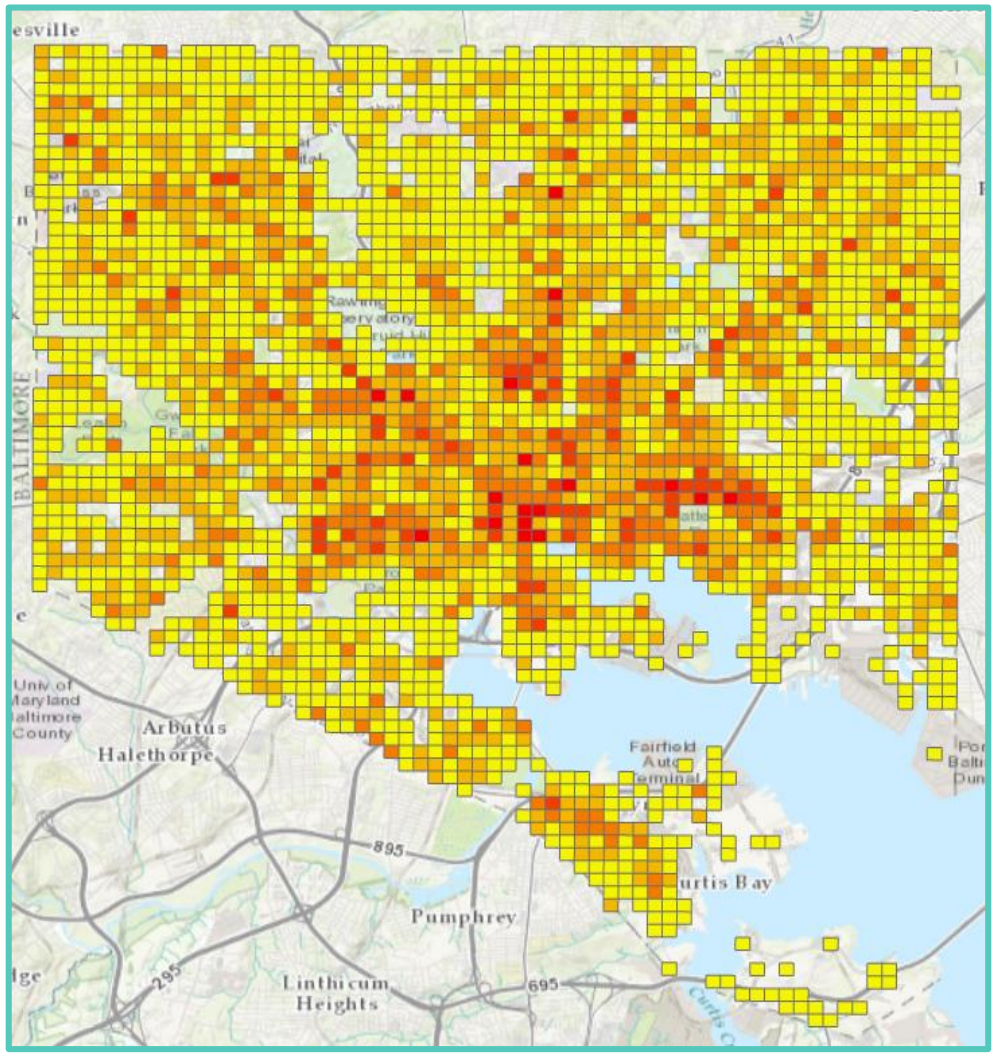
Cluster and Outlier Analysis

What about time?

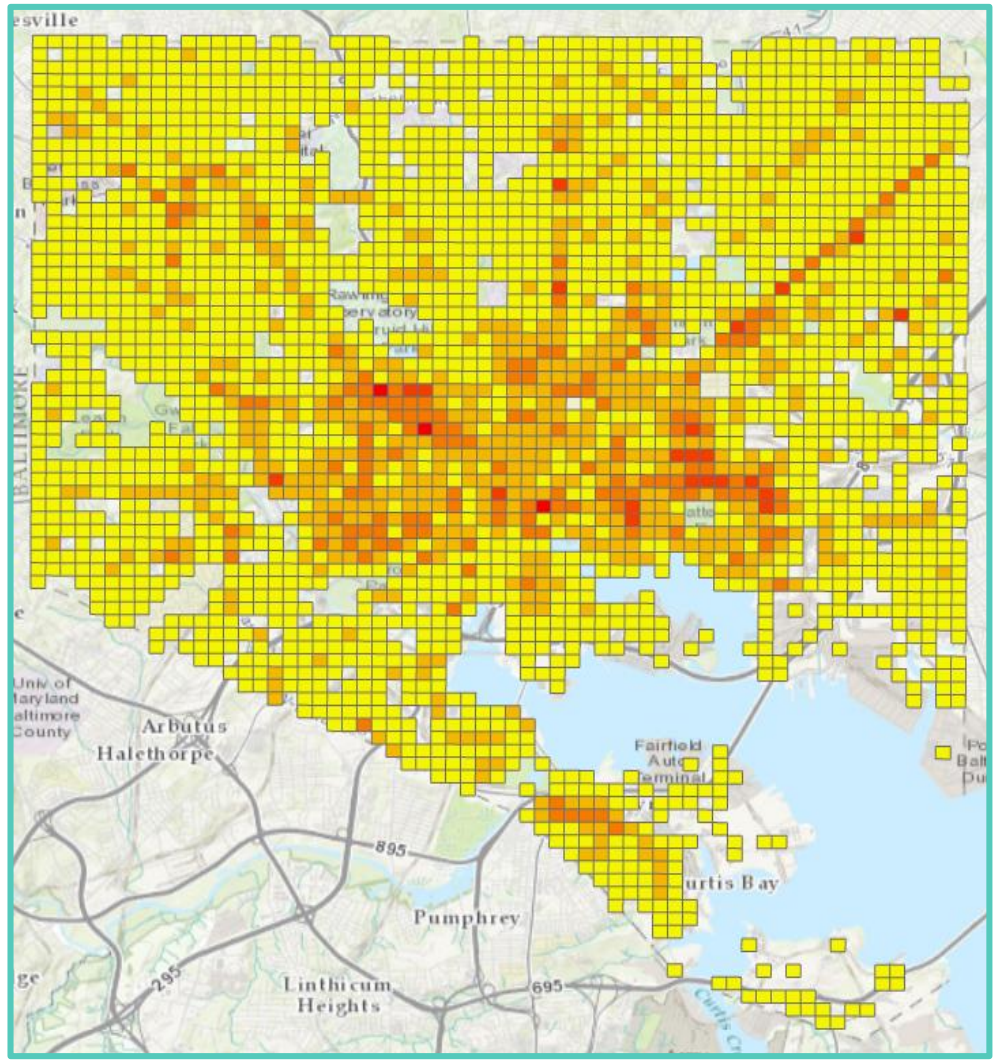


911 Calls

January 2015

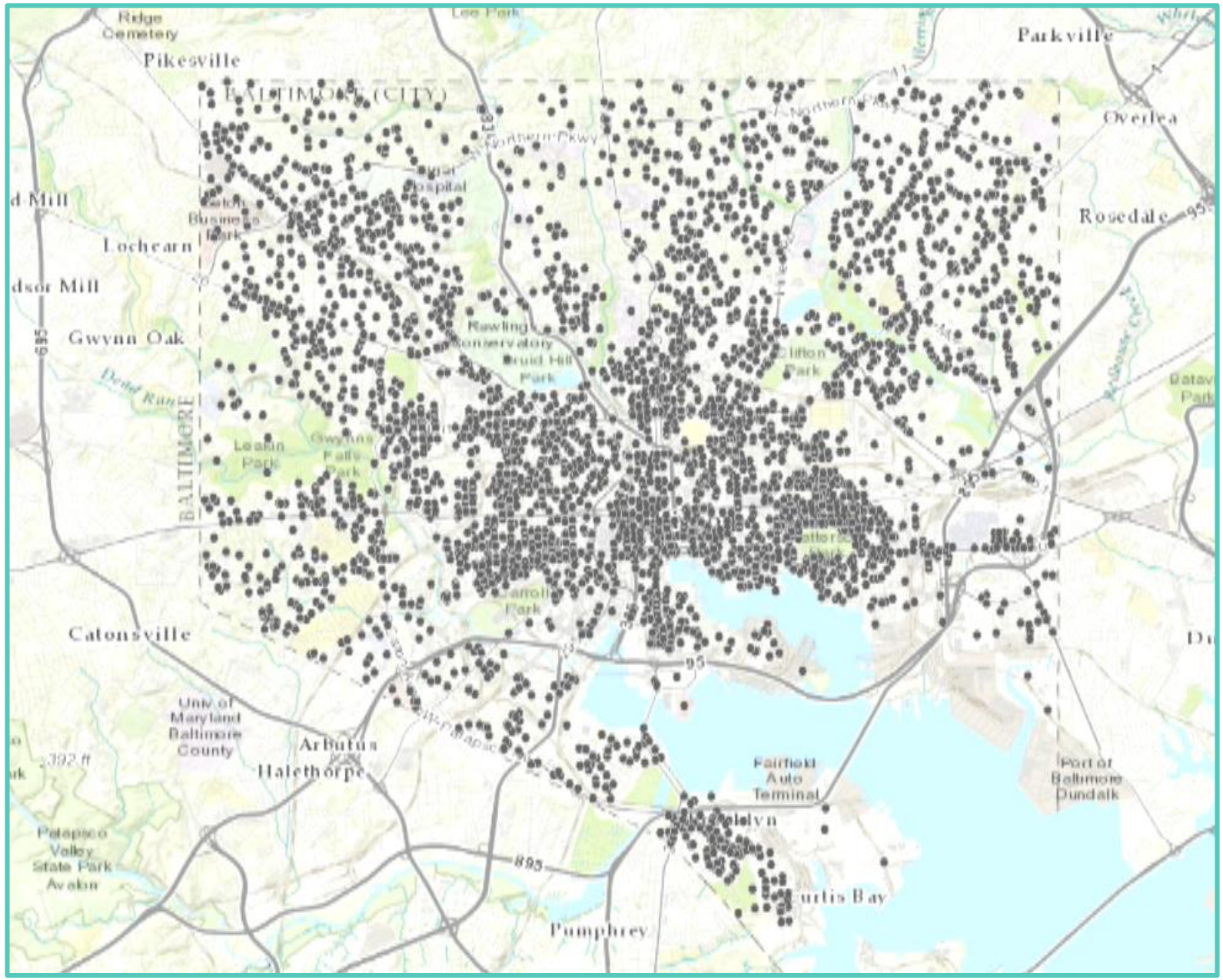


January 2016



Where have things changed? Is it meaningful?

911 Calls


Ridge Cemetery
Pikesville
Parkville
Overlea
Rosedale
Lochearn
Gwynn Oak
Catonsville
Univ of Maryland Baltimore County
Arbutus
Halethorpe
Fairfield Auto Terminal
Port of Baltimore Dundalk
Patapsco Valley State Park Avalon
Pumphrey
Curtis Bay
Clifton Park
Druid Hill Park
Leakin Park
Gwynns Falls Park
Carroll Park
95
895

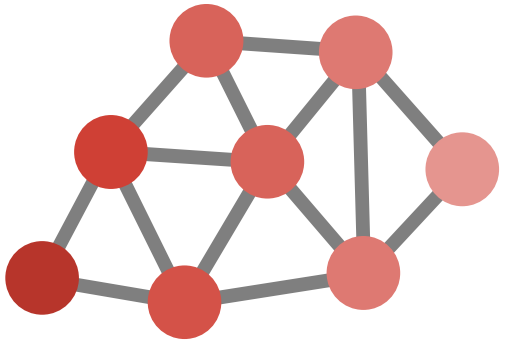
NERD ALERT

"... everything is related to everything else, but near things are more related than distant things."
– Tobler's first law of geography
Redlands
esri

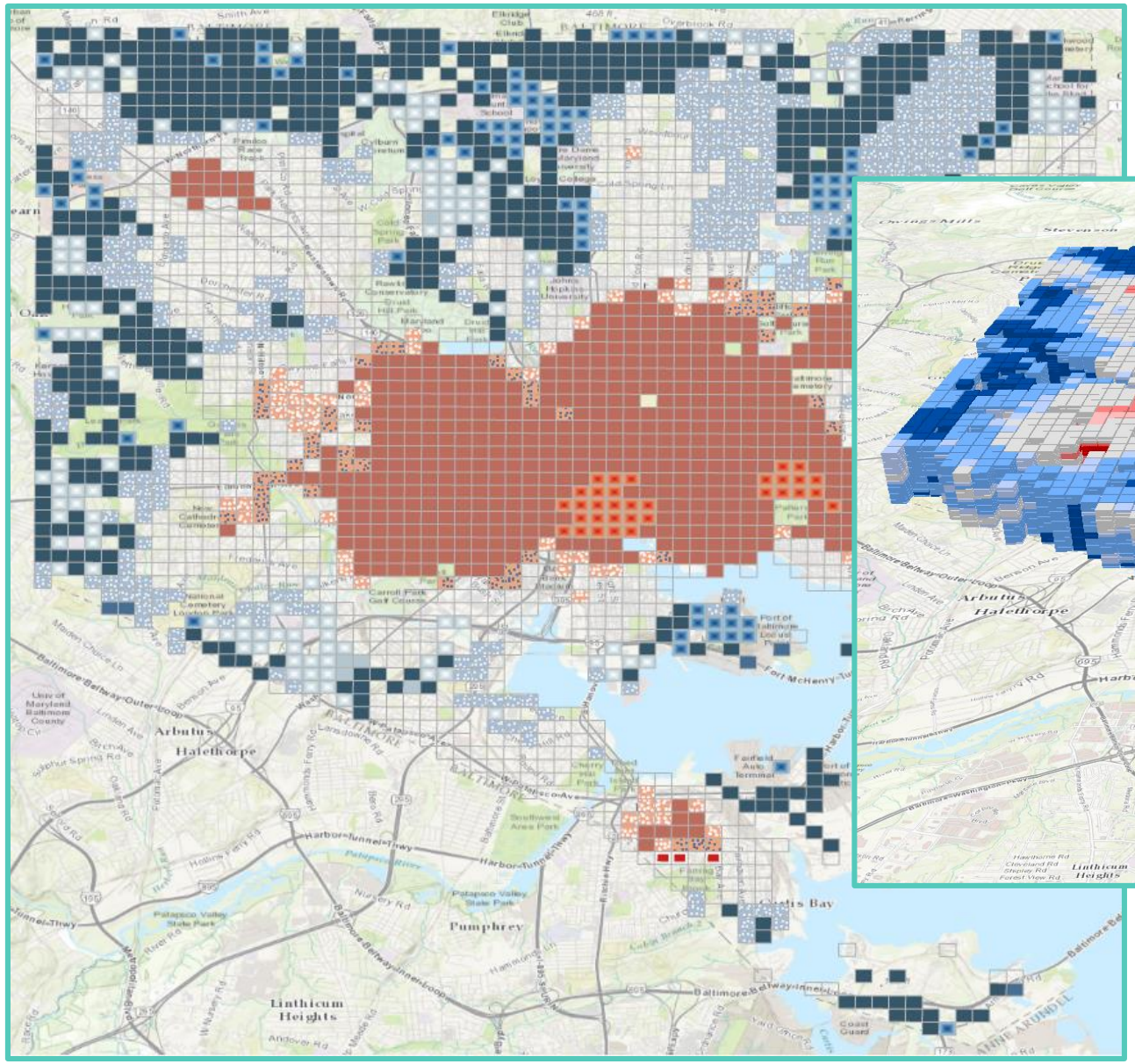
"...everything is related to everything else, but

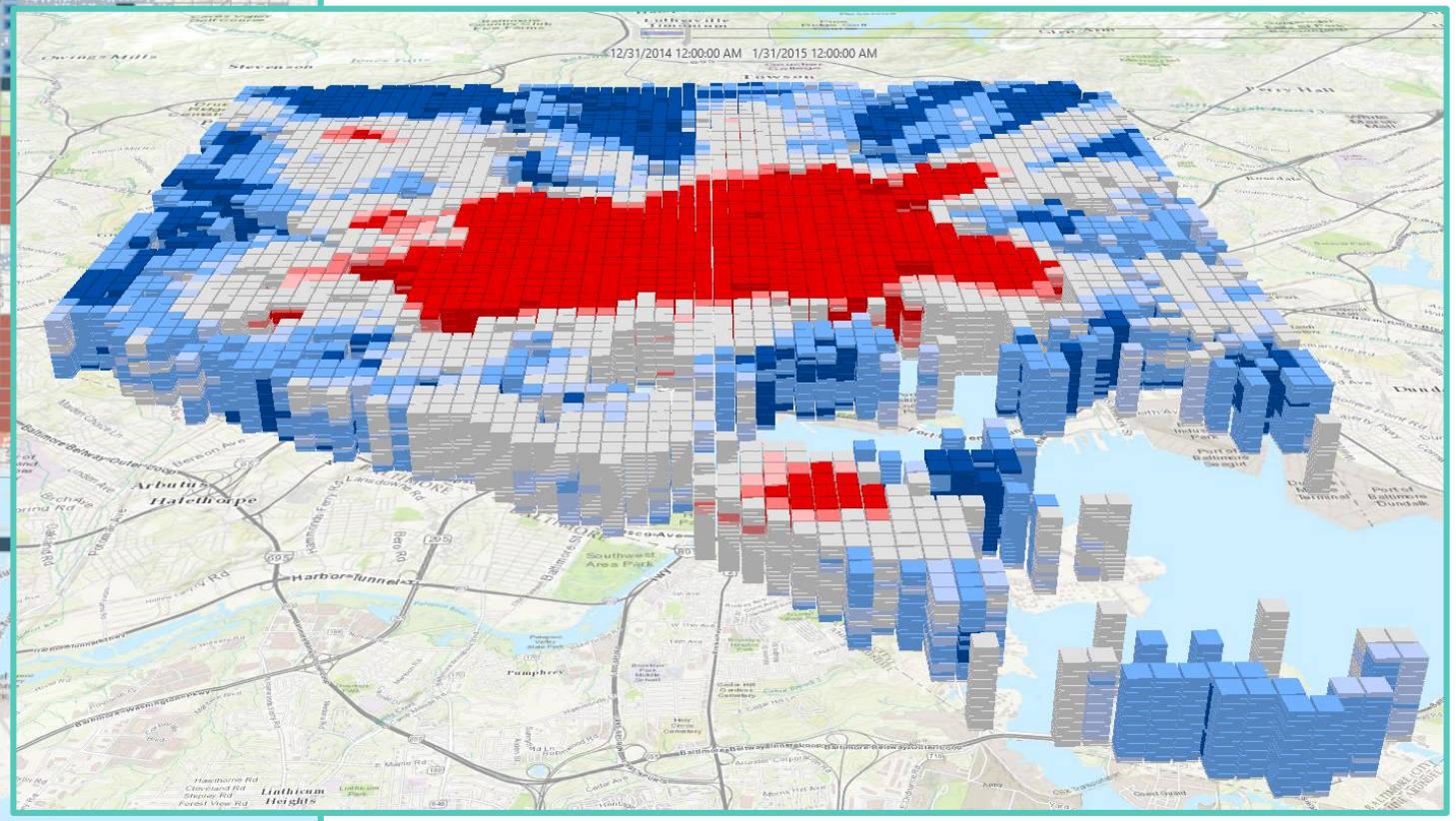
near and recent

things are more related than **distant** things."



Quantifying Spatiotemporal Clusters

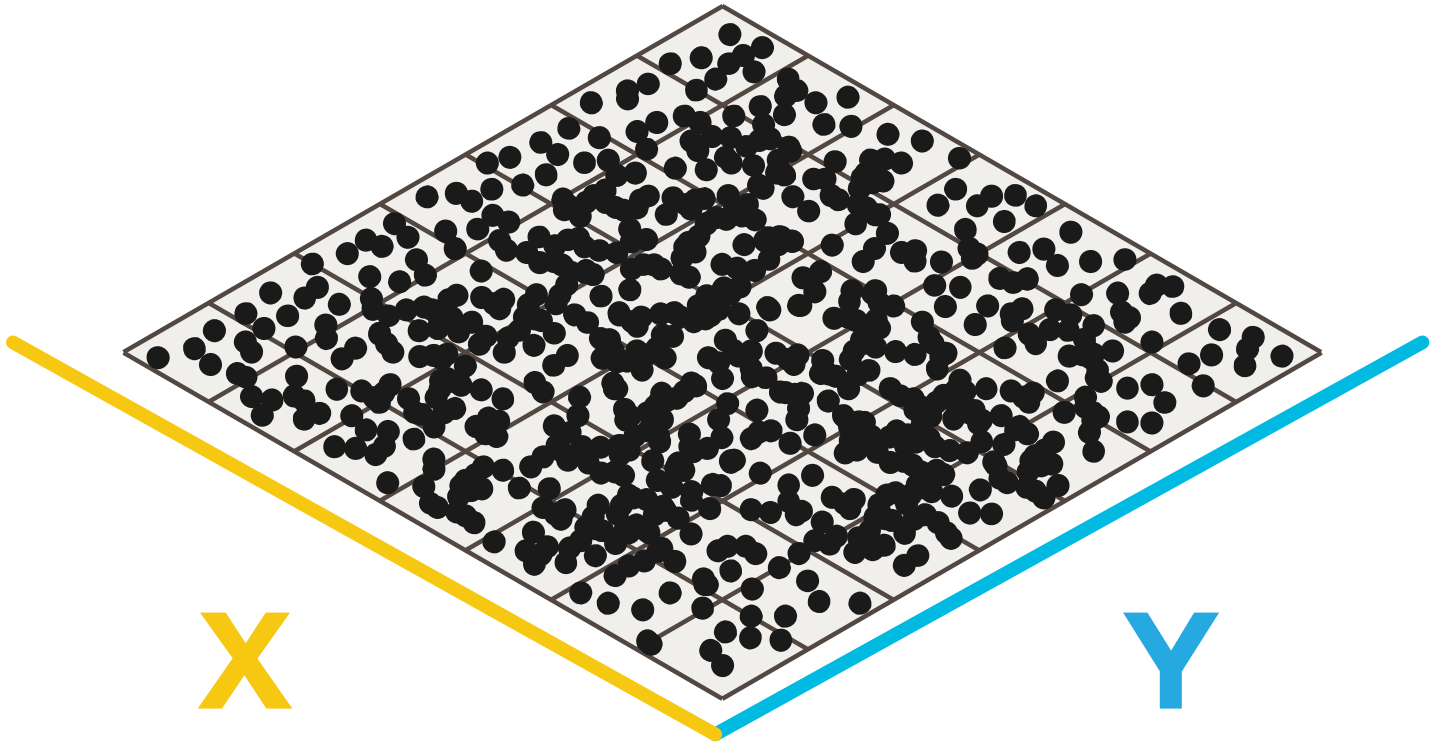


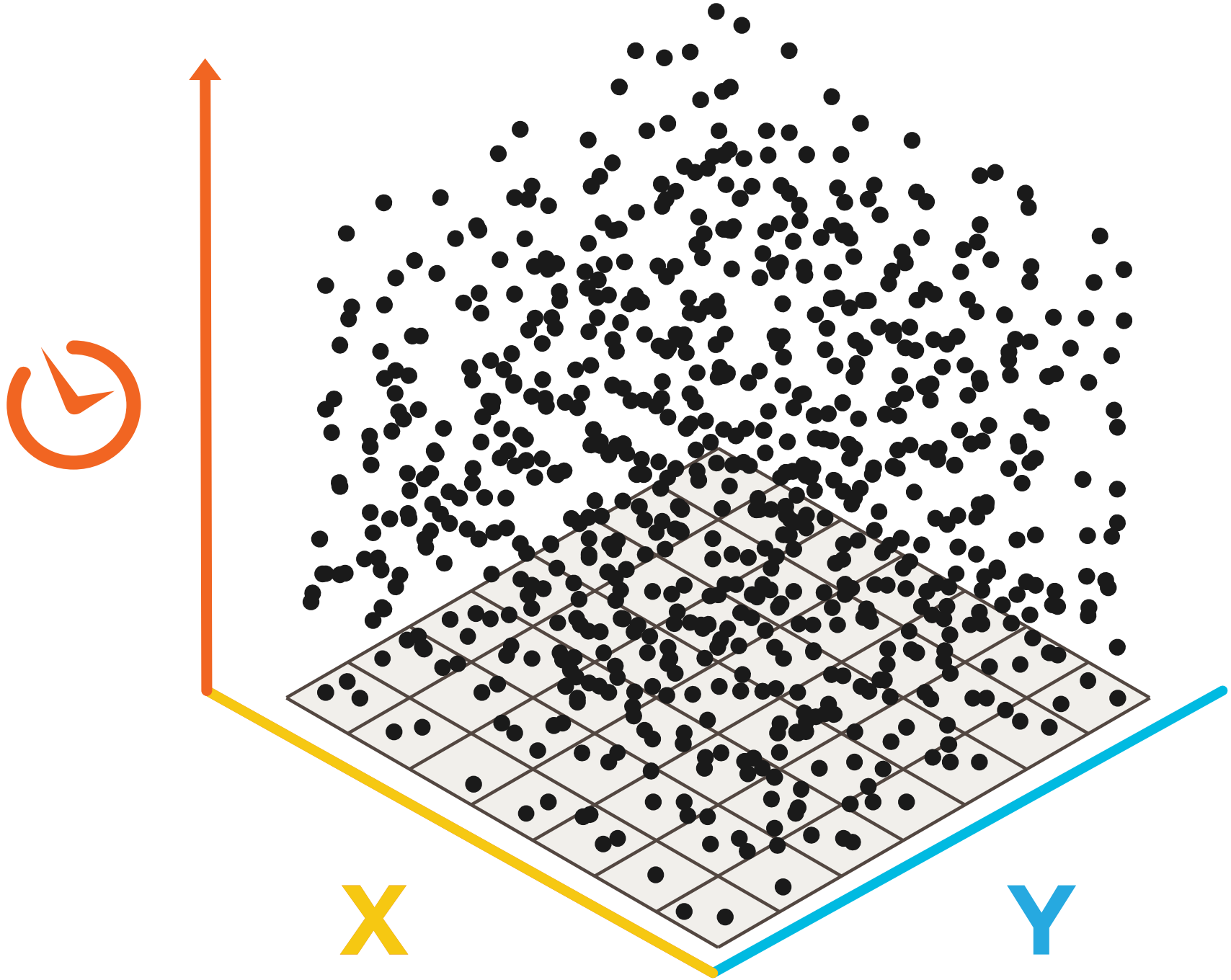


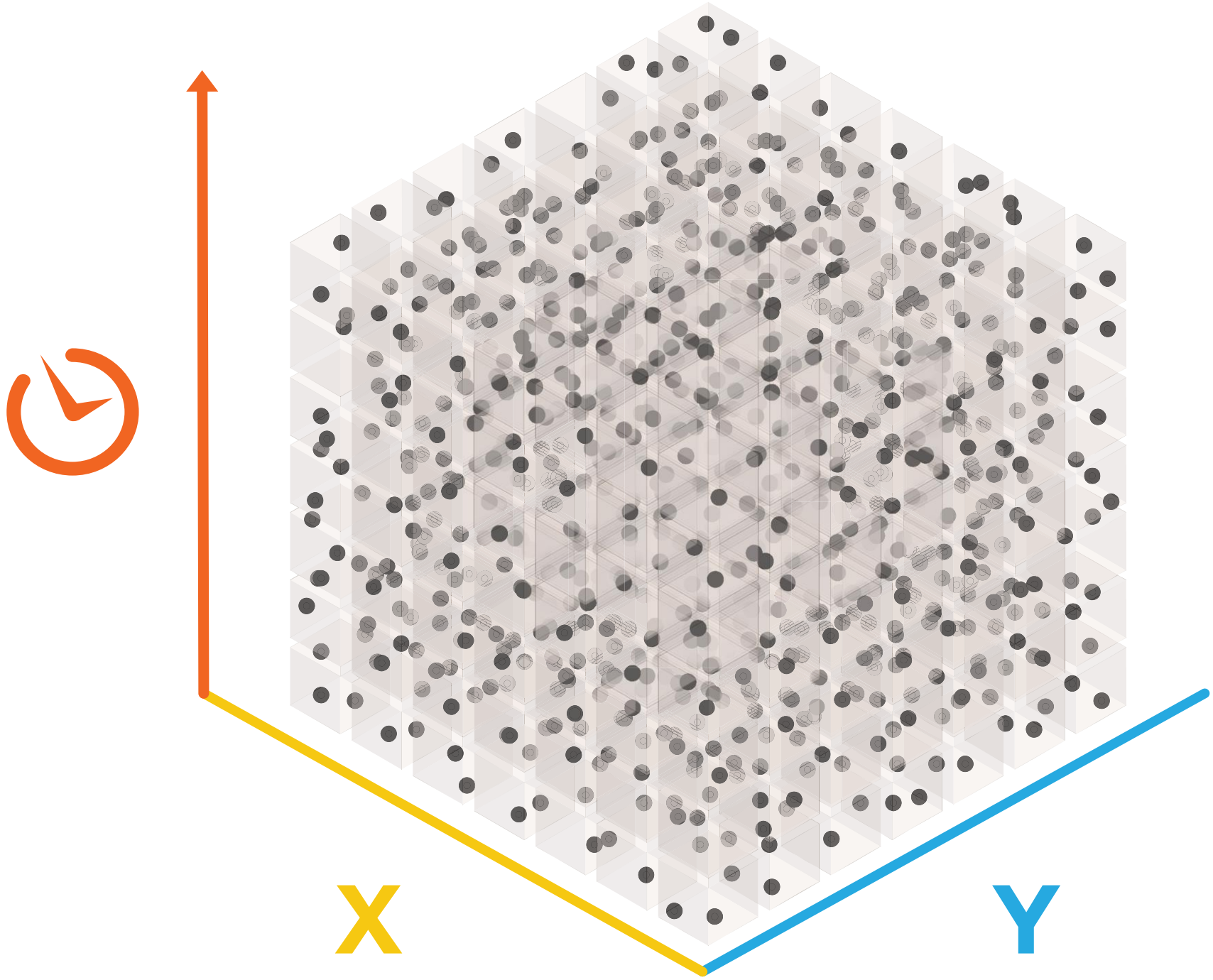
The Space Time Pattern Mining Tools

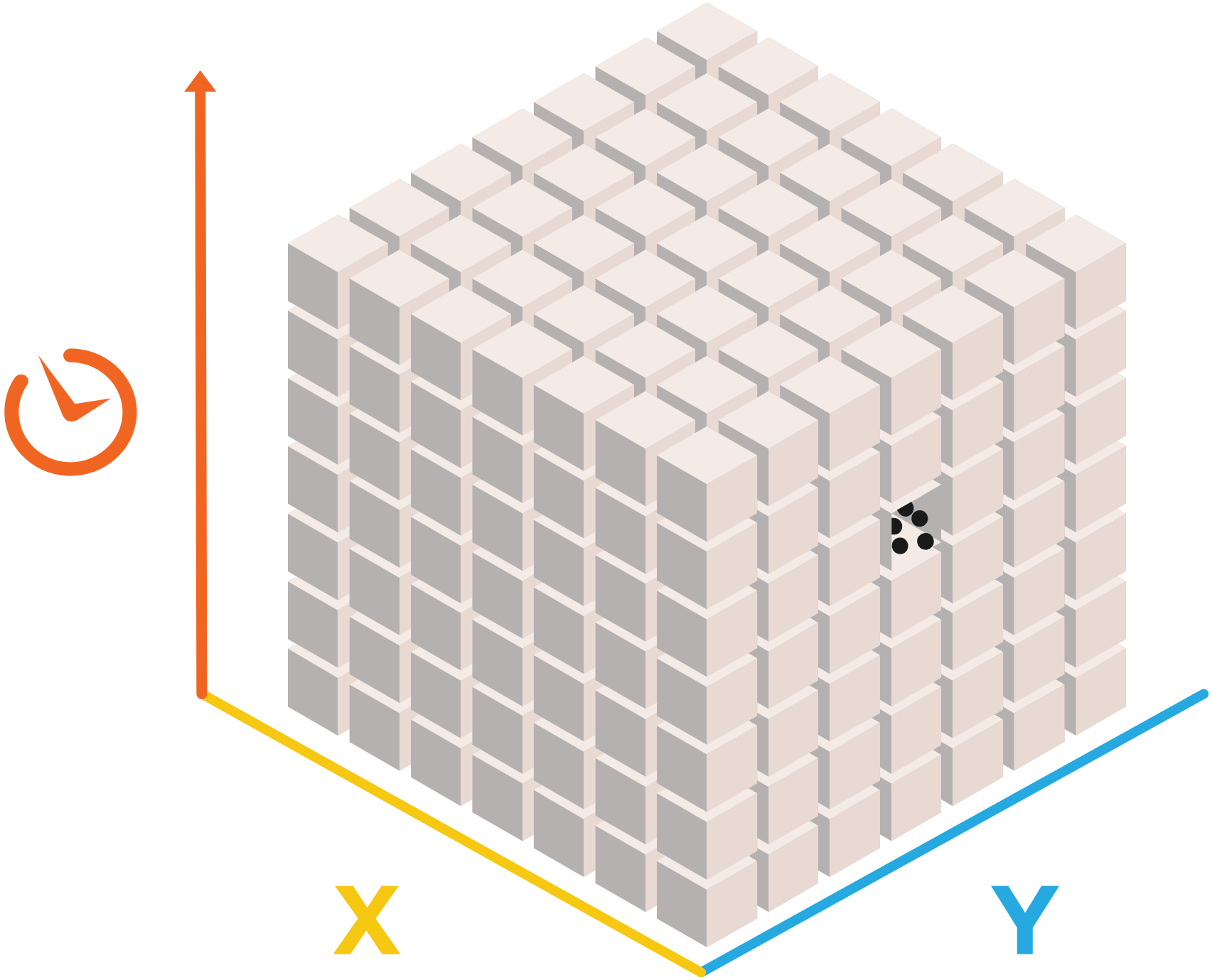
Create Space Time Cube By Aggregating Points

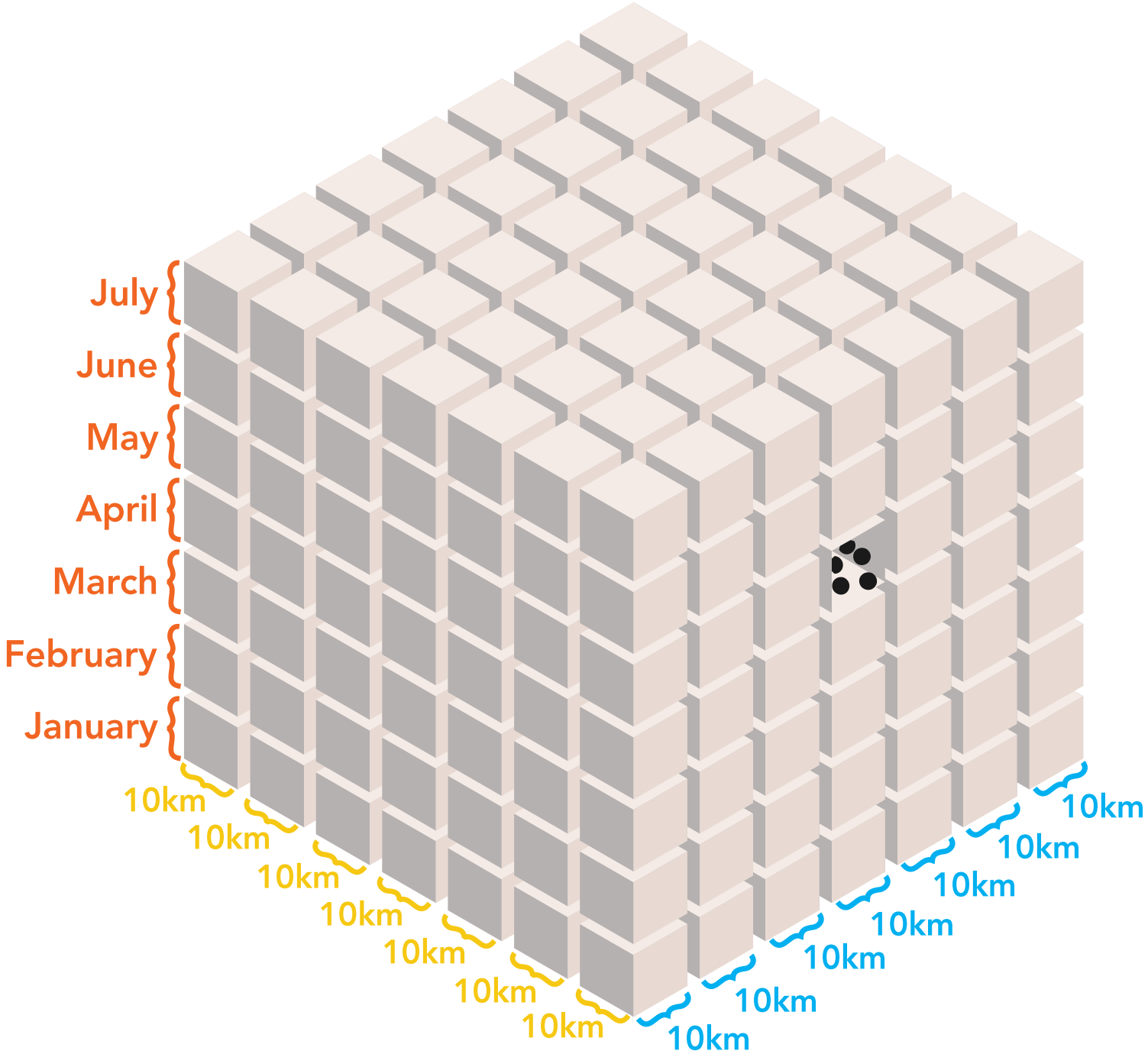
aggregates a set of points into space-time bins, counting the number of points and optionally calculating statistics for attributes


X
Y

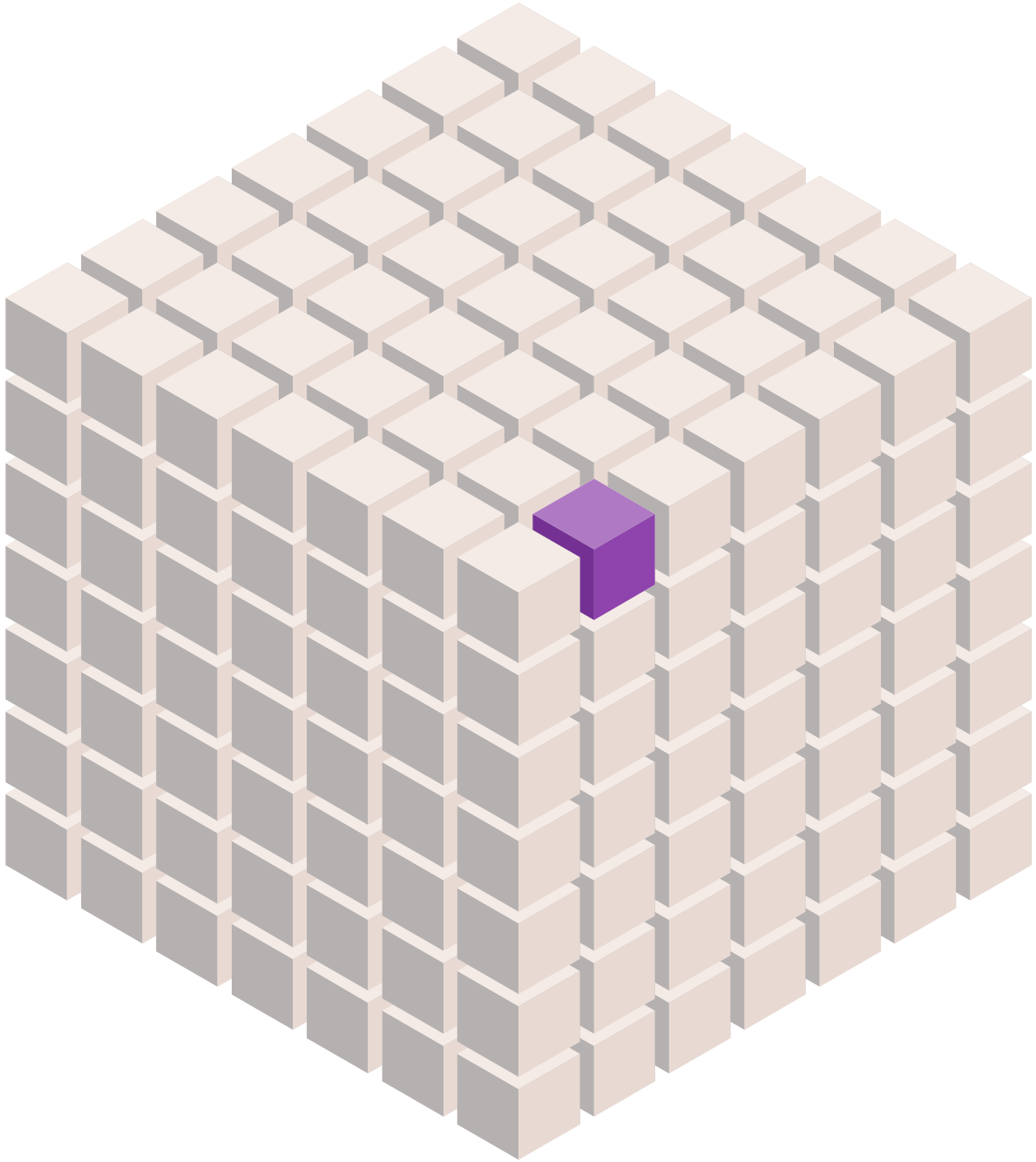

X
Y


X
Y

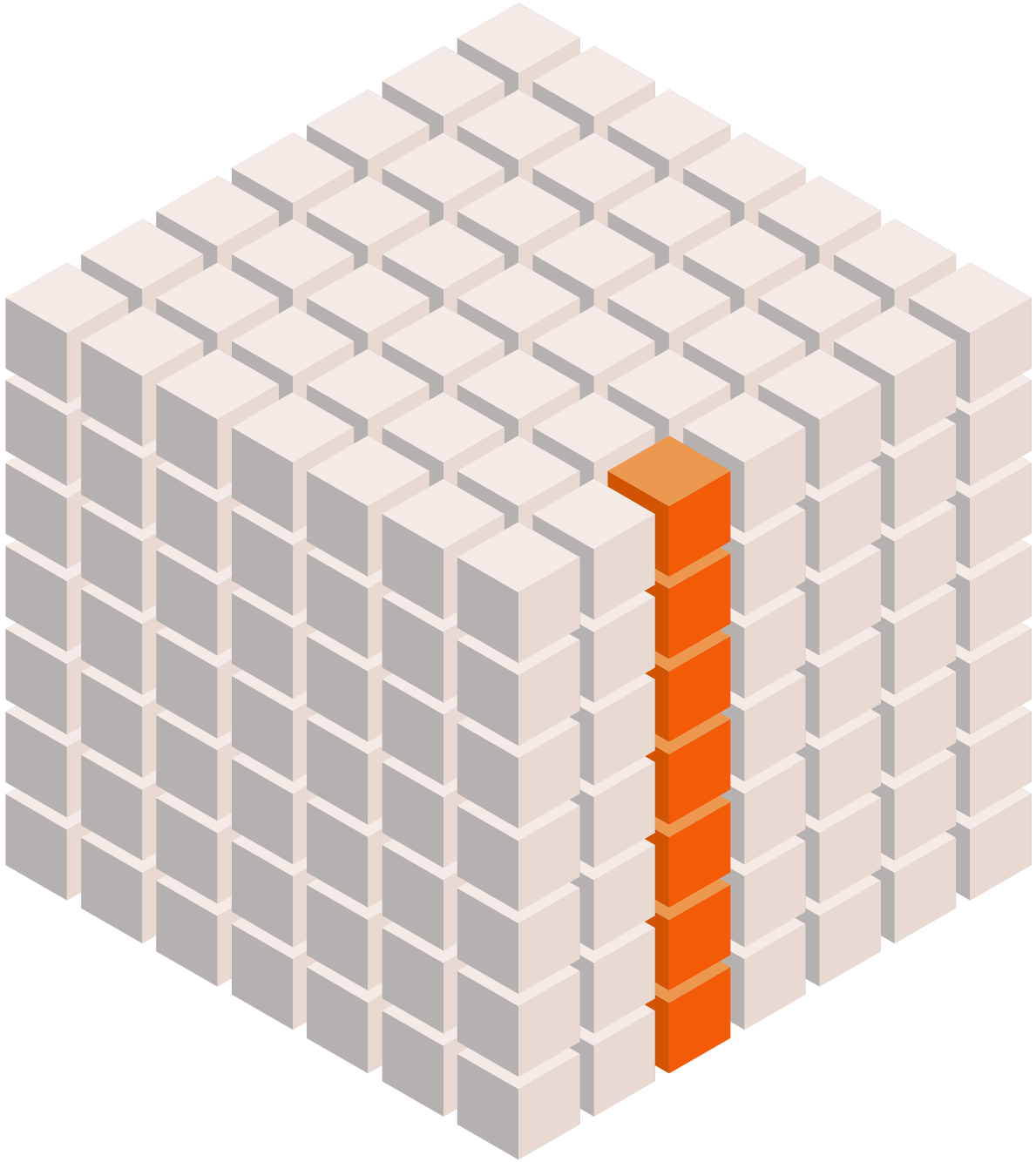

X
Y


July
June
May
April
March
February
January
10km
10km
10km
10km
10km
10km
10km
10km
10km
10km
10km
10km

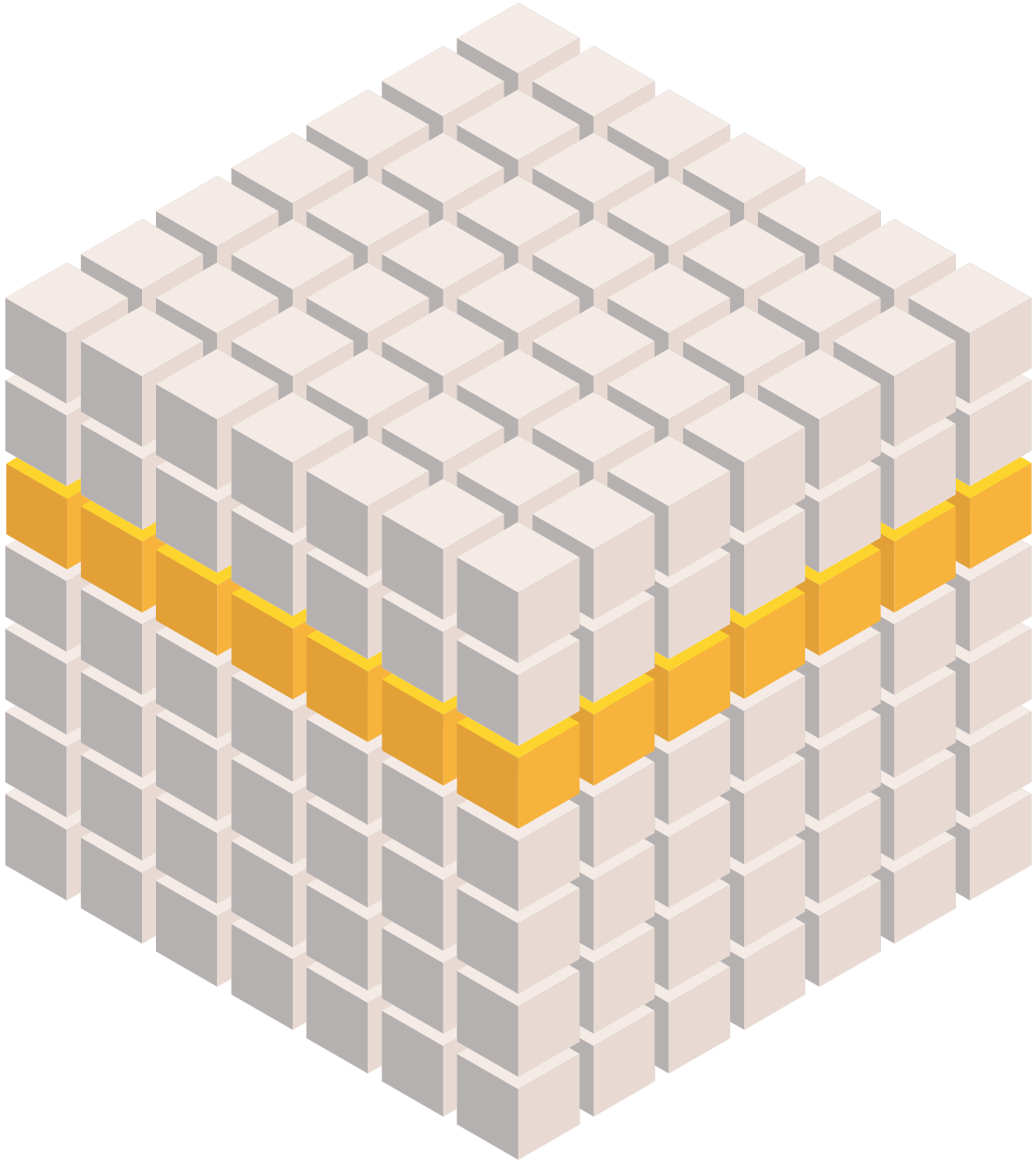
bin



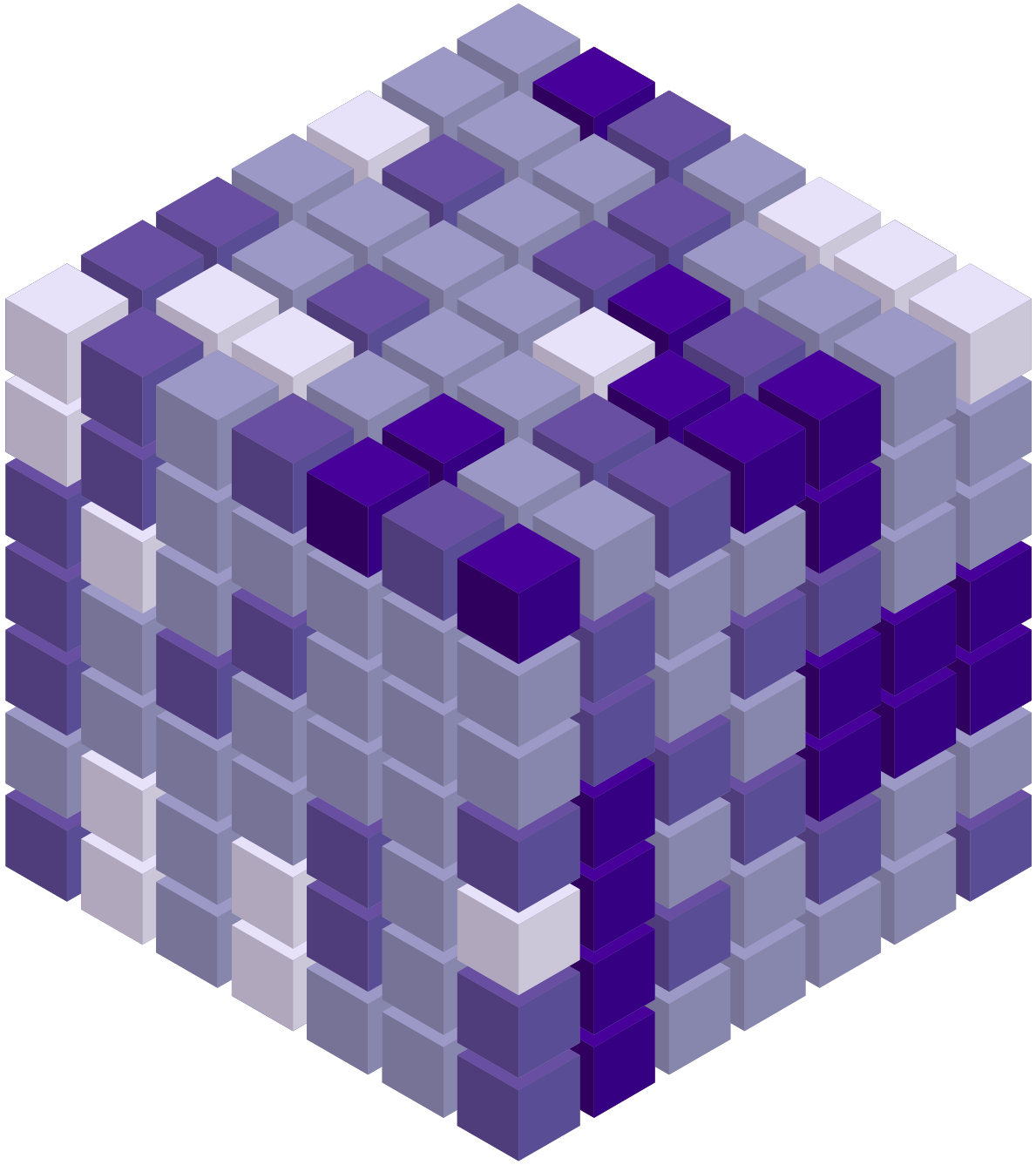
location



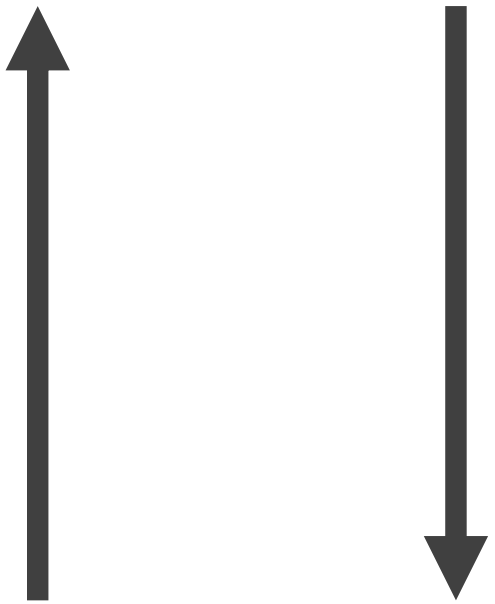
time slice

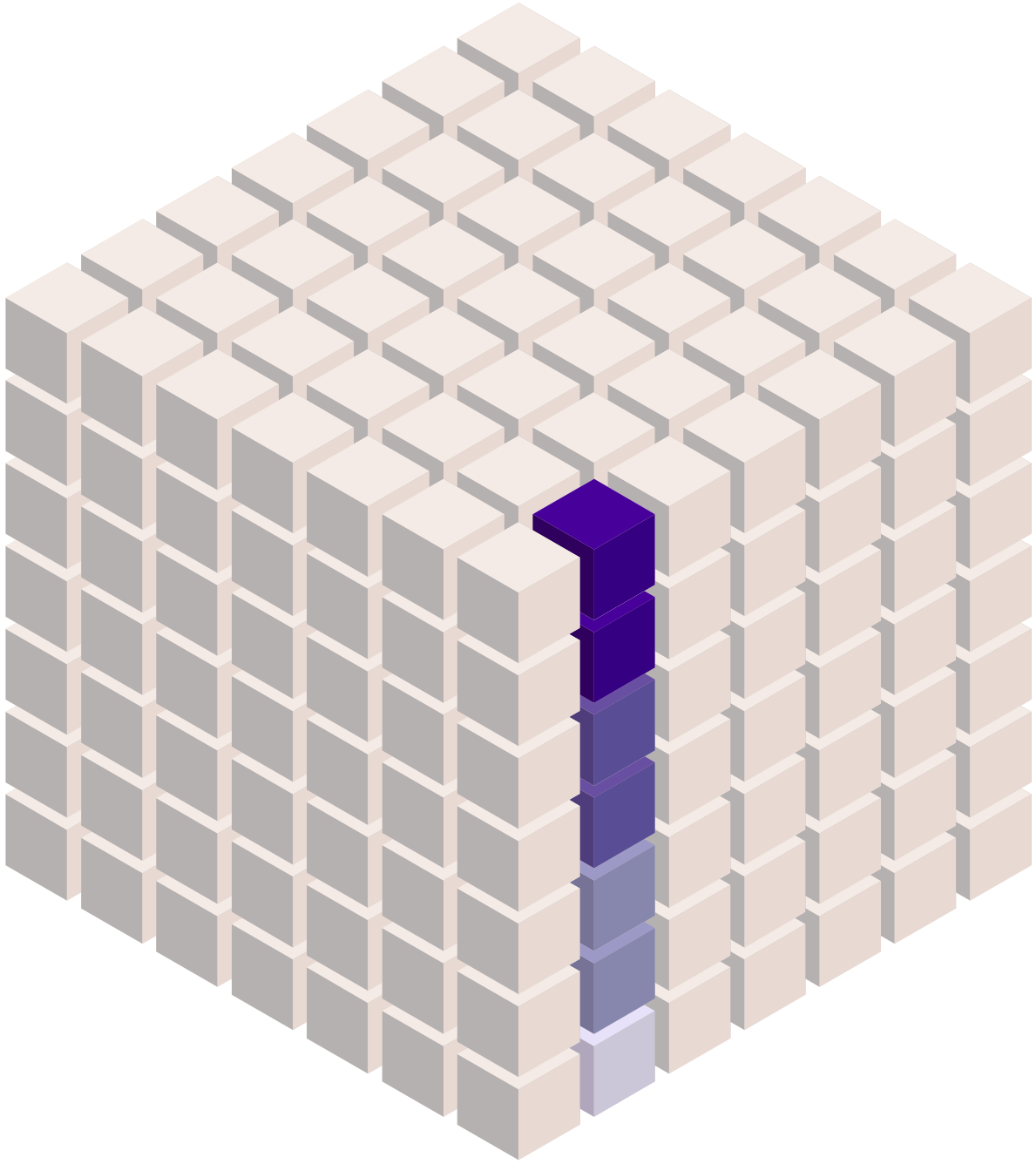


counts



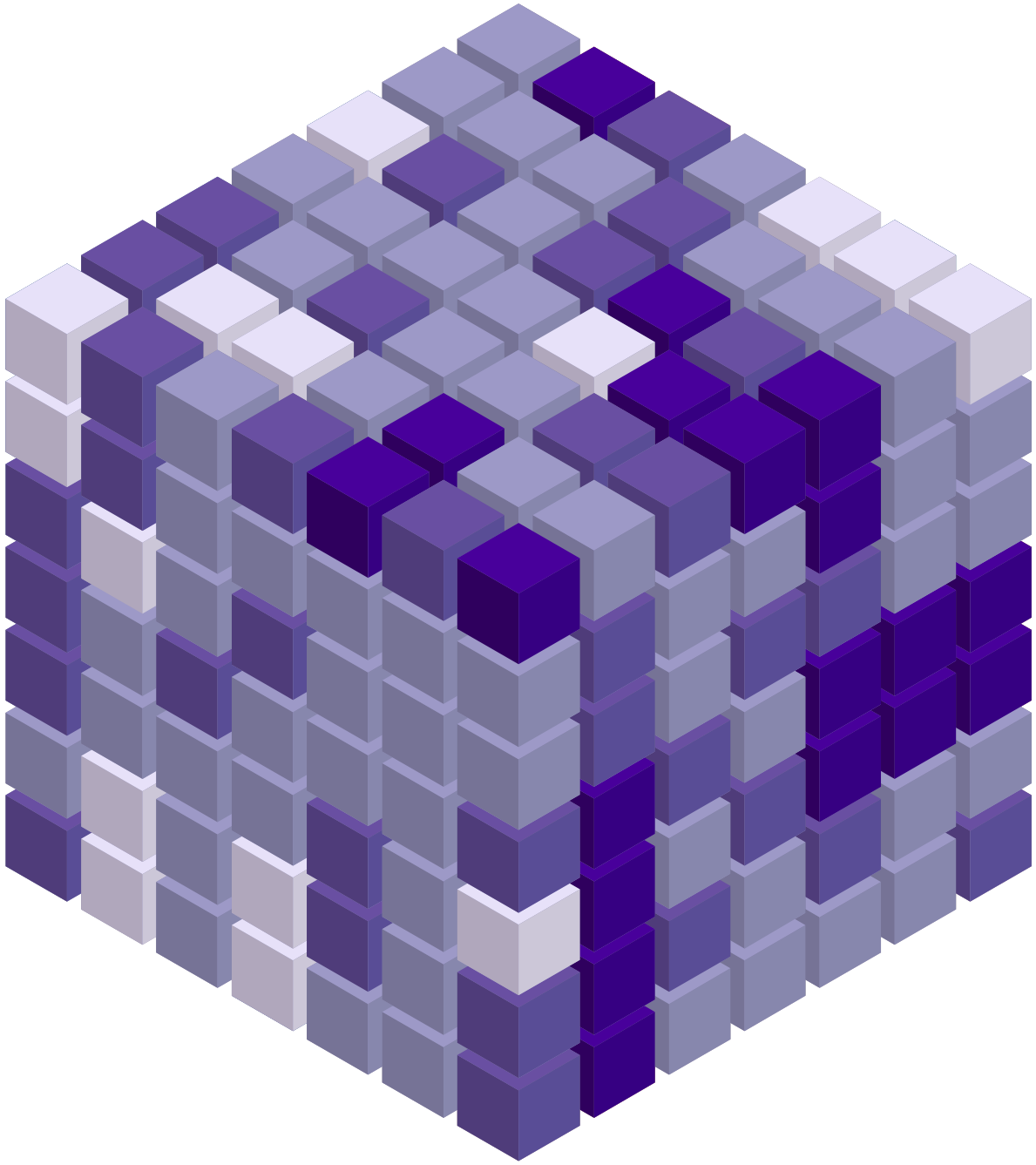
trend analysis



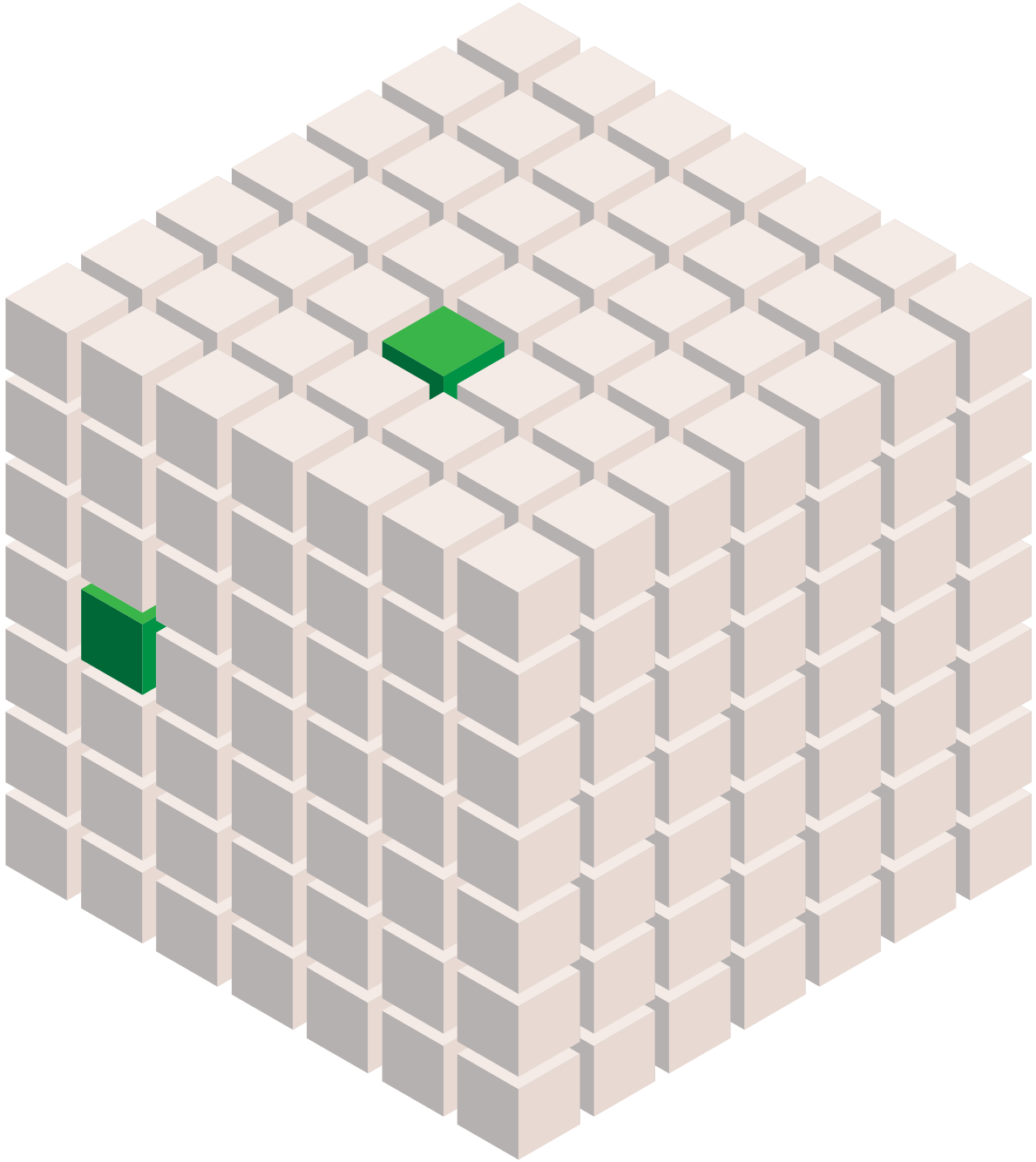


summary fields

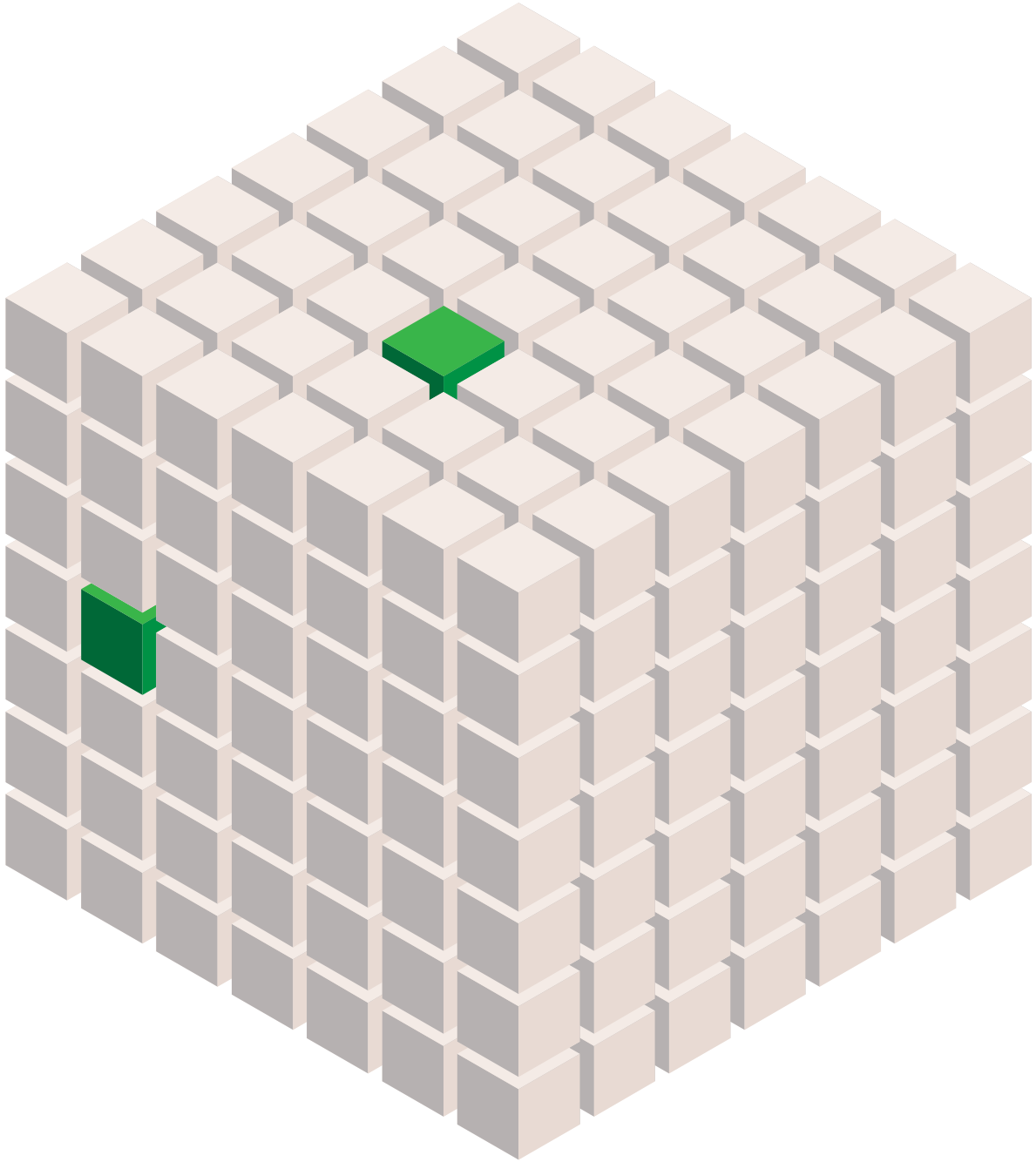
sum
mean
median
min
max
standard deviation



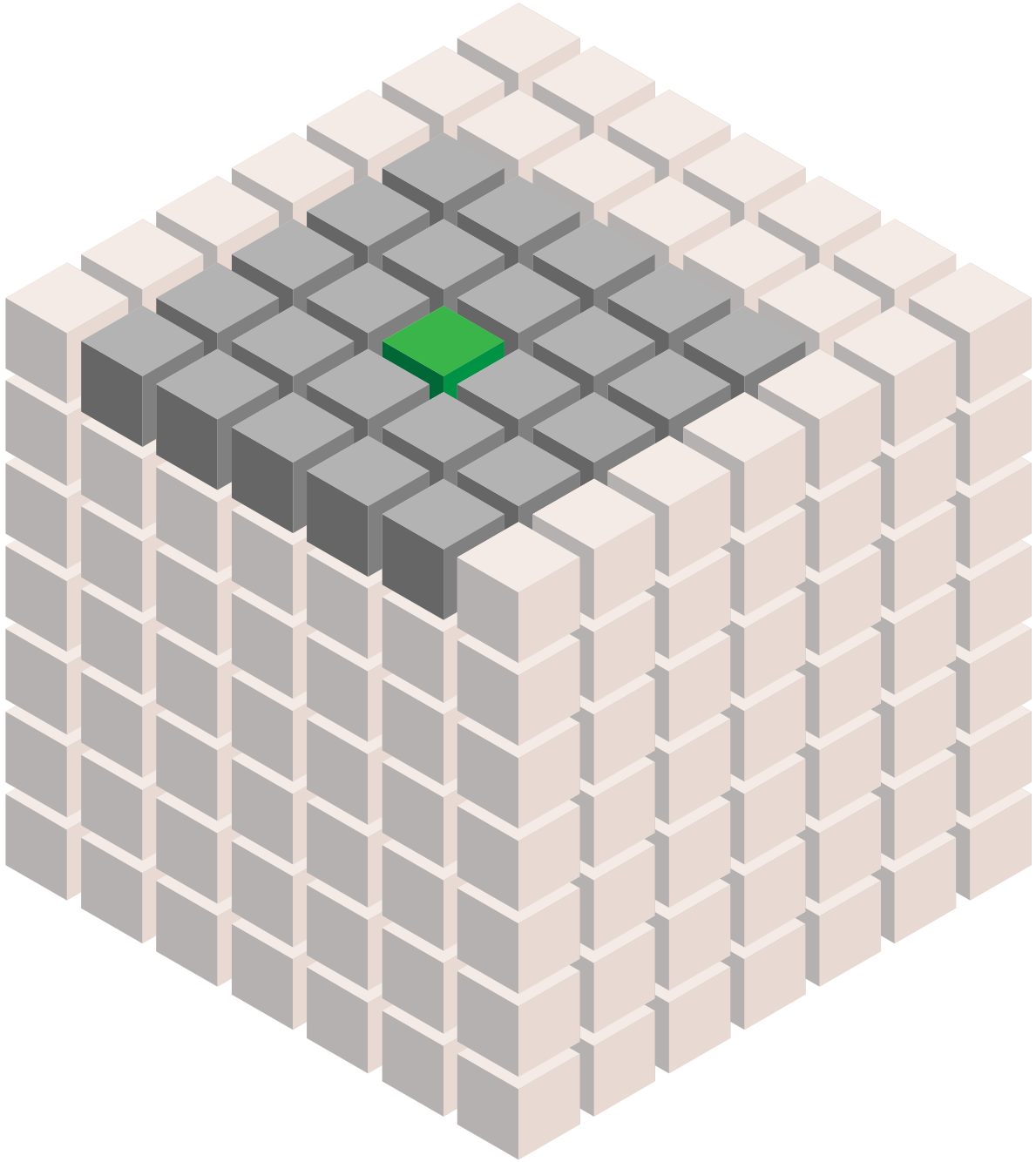
filling empty bins



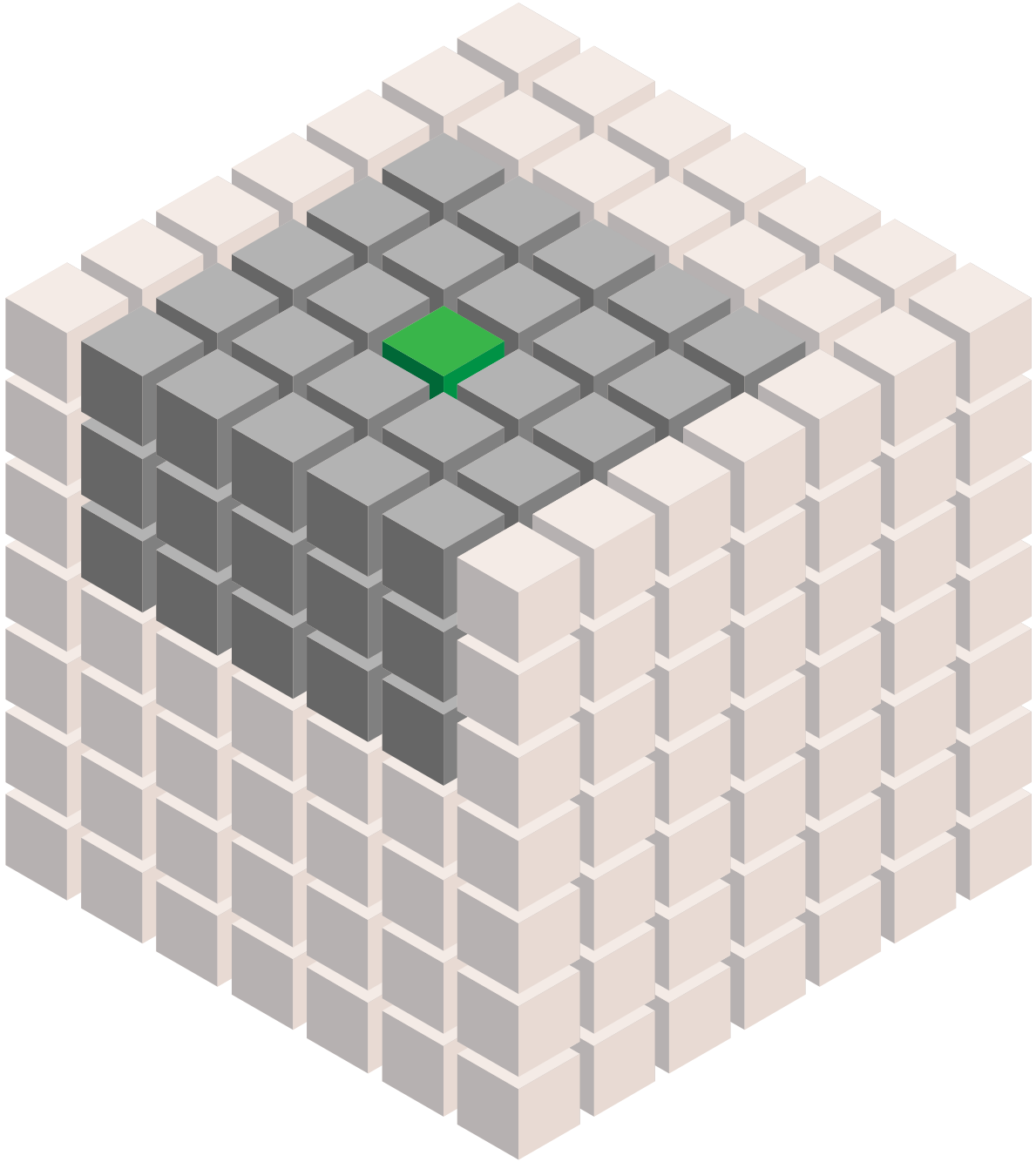
zeros



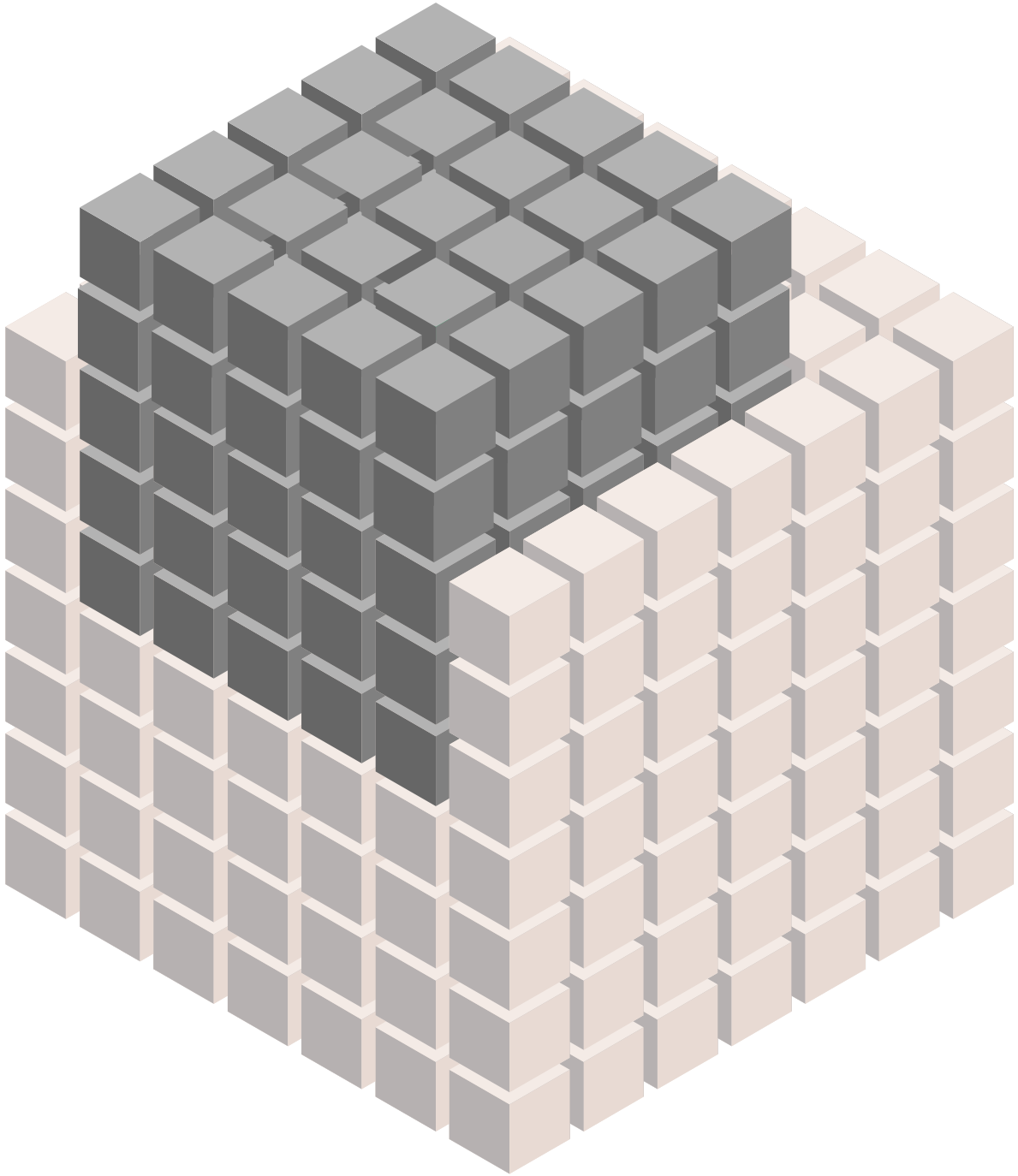
spatial neighbors



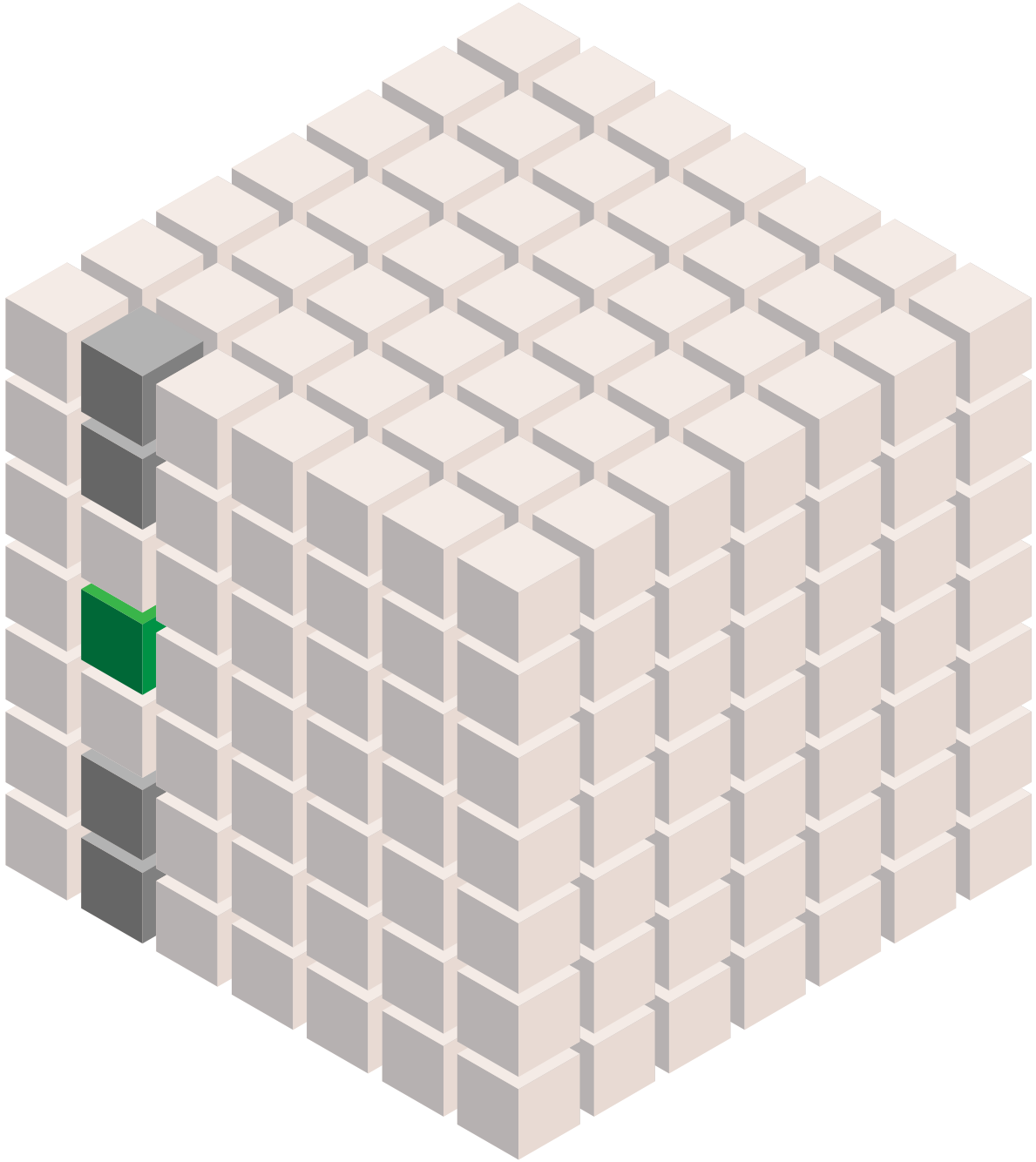
space time neighbors



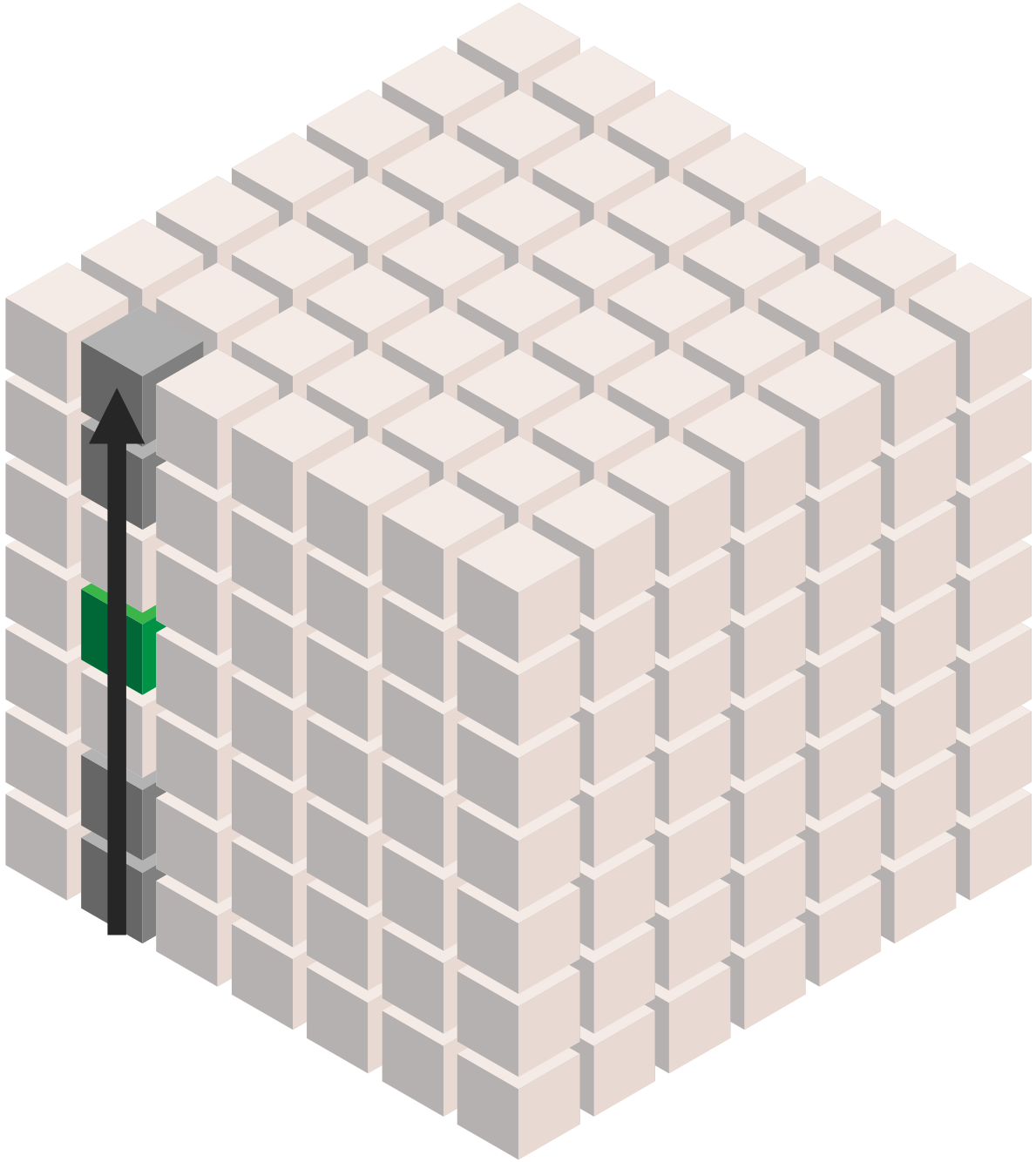
space time neighbors

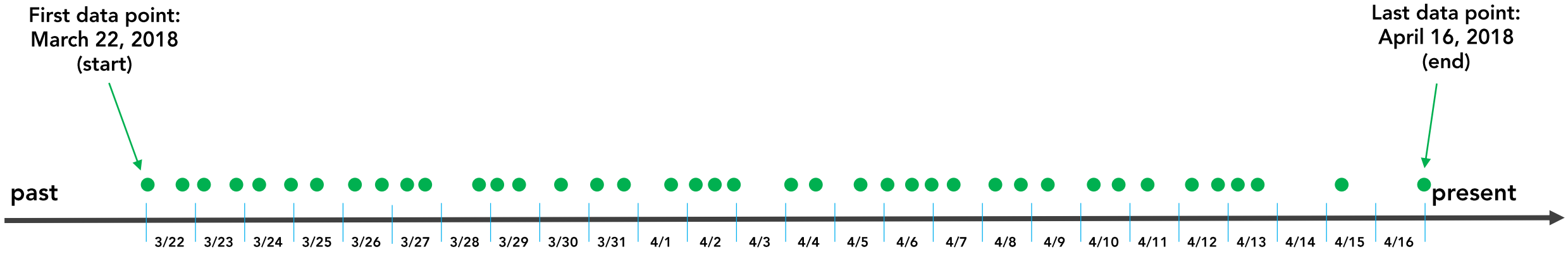


temporal neighbors

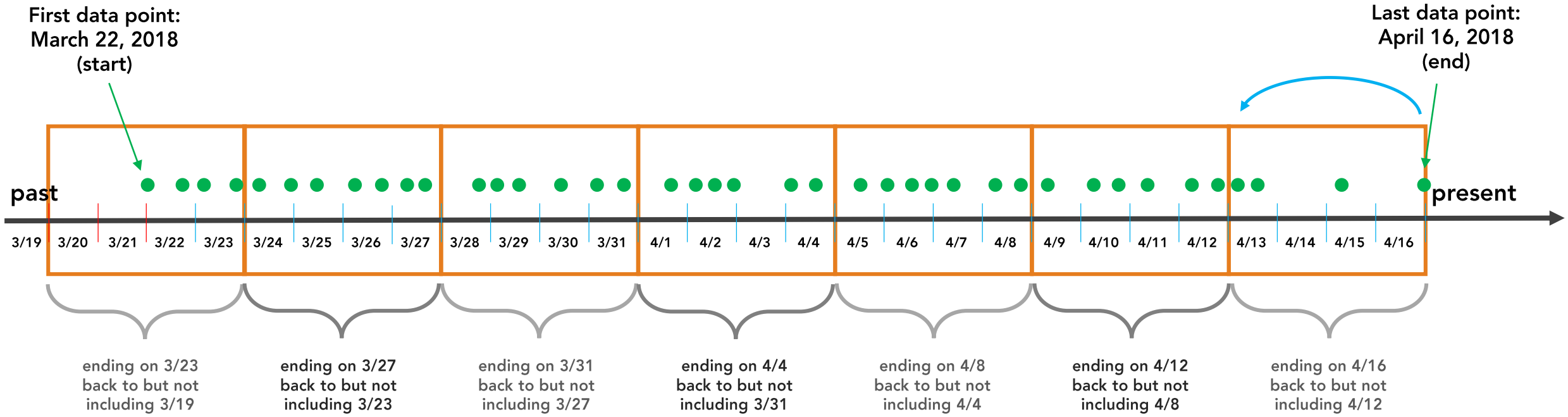


temporal neighbors

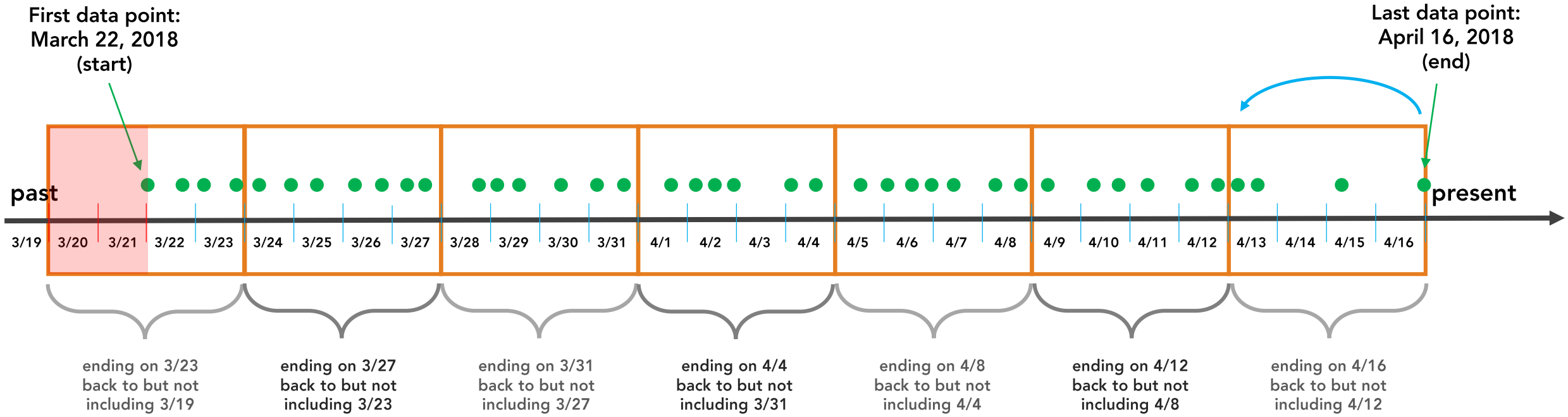



First data point:
March 22, 2018
(start)
Last data point:
April 16, 2018
(end)
past
present
3/22
3/23
3/24
3/25
3/26
3/27
3/28
3/29
3/30
3/31
4/1
4/2
4/3
4/4
4/5
4/6
4/7
4/8
4/9
4/10
4/11
4/12
4/13
4/14
4/15
4/16

End Time


First data point:
March 22, 2018
(start)
Last data point:
April 16, 2018
(end)
past
present
3/19
3/20
3/21
3/22
3/23
3/24
3/25
3/26
3/27
3/28
3/29
3/30
3/31
4/1
4/2
4/3
4/4
4/5
4/6
4/7
4/8
4/9
4/10
4/11
4/12
4/13
4/14
4/15
4/16
ending on 3/23 back to but not including 3/19
ending on 3/27 back to but not including 3/23
ending on 3/31 back to but not including 3/27
ending on 4/4 back to but not including 3/31
ending on 4/8 back to but not including 4/4
ending on 4/12 back to but not including 4/8
ending on 4/16 back to but not including 4/12

End Time


First data point:
March 22, 2018
(start)
Last data point:
April 16, 2018
(end)
past
present
3/19
3/20
3/21
3/22
3/23
3/24
3/25
3/26
3/27
3/28
3/29
3/30
3/31
4/1
4/2
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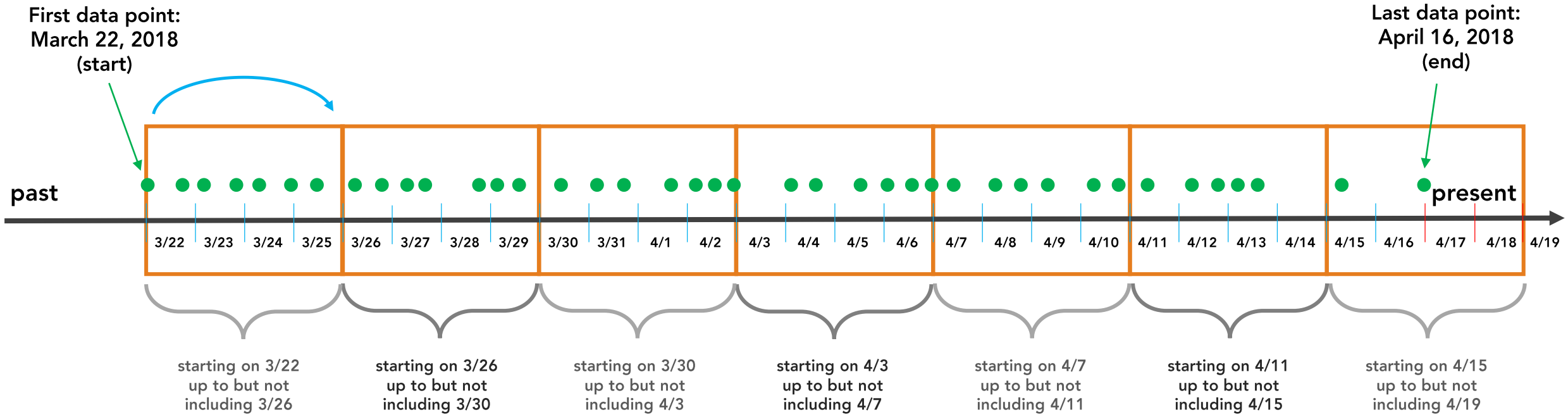
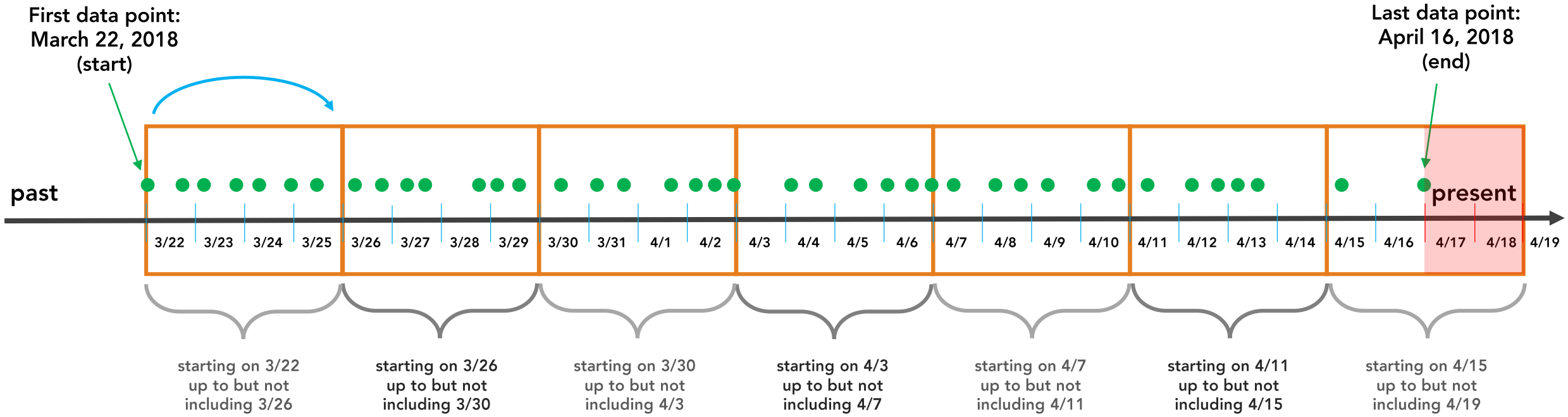
4/4
4/5
4/6
4/7
4/8
4/9
4/10
4/11
4/12
4/13
4/14
4/15
4/16
ending on 3/23 back to but not including 3/19
ending on 3/27 back to but not including 3/23
ending on 3/31 back to but not including 3/27
ending on 4/4 back to but not including 3/31
ending on 4/8 back to but not including 4/4
ending on 4/12 back to but not including 4/8
ending on 4/16 back to but not including 4/12

Start Time


First data point:
March 22, 2018
(start)
Last data point:
April 16, 2018
(end)
past
present
3/22
3/23
3/24
3/25
3/26
3/27
3/28
3/29
3/30
3/31
4/1
4/2
4/3
4/4
4/5
4/6
4/7
4/8
4/9
4/10
4/11
4/12
4/13
4/14
4/15
4/16
4/17
4/18
4/19
starting on 3/22 up to but not including 3/26
starting on 3/26 up to but not including 3/30
starting on 3/30 up to but not including 4/3
starting on 4/3 up to but not including 4/7
starting on 4/7 up to but not including 4/11
starting on 4/11 up to but not including 4/15
starting on 4/15 up to but not including 4/19

Start Time


First data point:
March 22, 2018
(start)
Last data point:
April 16, 2018
(end)
past
present
3/22
3/23
3/24
3/25
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3/27
3/28
3/29
3/30
3/31
4/1
4/2
4/3
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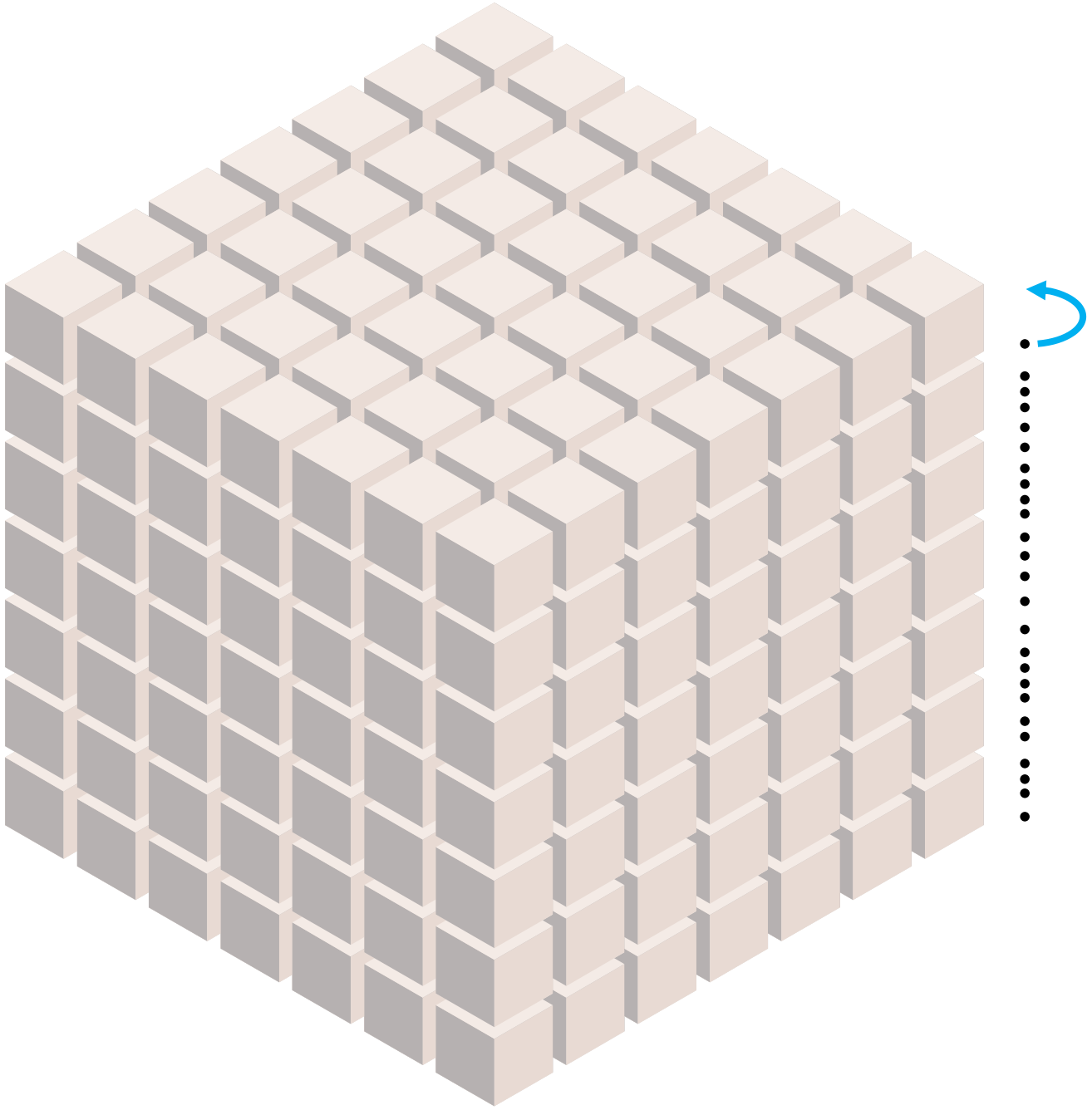
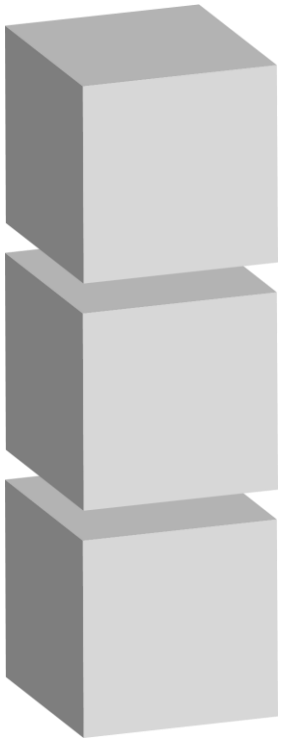
4/7
4/8
4/9
4/10
4/11
4/12
4/13
4/14
4/15
4/16
4/17
4/18
4/19
starting on 3/22 up to but not including 3/26
starting on 3/26 up to but not including 3/30
starting on 3/30 up to but not including 4/3
starting on 4/3 up to but not including 4/7
starting on 4/7 up to but not including 4/11
starting on 4/11 up to but not including 4/15
starting on 4/15 up to but not including 4/19

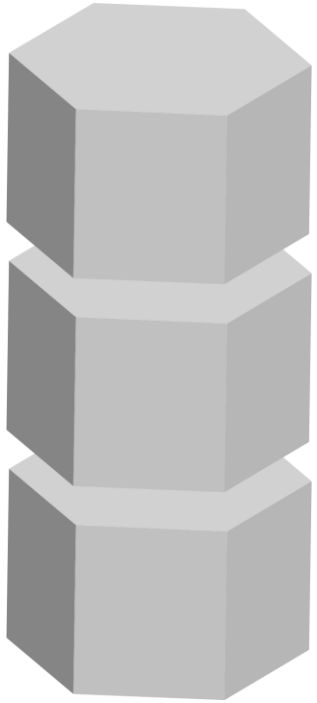
Temporal Bias



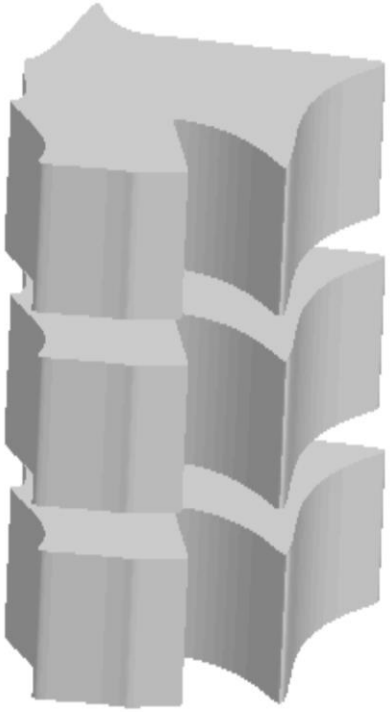
Aggregation Options



fishnet grid



hexagon grid



New!

defined locations

Create Space Time Cube From Defined Locations

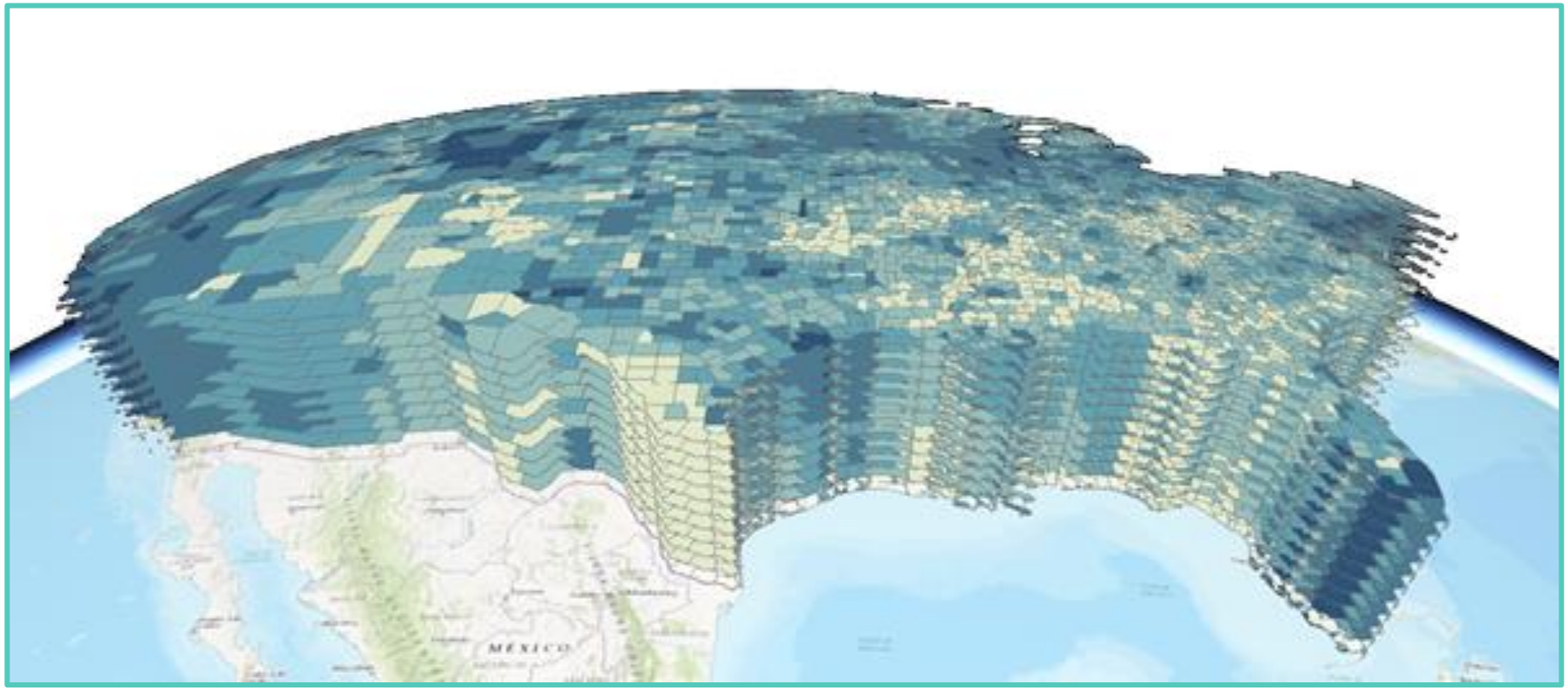
structures panel data or station data where geography does not change but attributes change over time into space-time bins

Data can be one set of features with a related table containing attributes over time

ID	DateTime	Reading
GSB001	09/14/2015 00:00:00	03.14
GSB001	09/14/2015 05:00:00	15.92
GSB001	09/14/2015 10:00:00	69.35
GSB002	09/14/2015 00:00:00	89.79
GSB002	09/14/2015 05:00:00	32.38
GSB002	09/14/2015 10:00:00	46.26
GSB003	09/14/2015 00:00:00	43.38

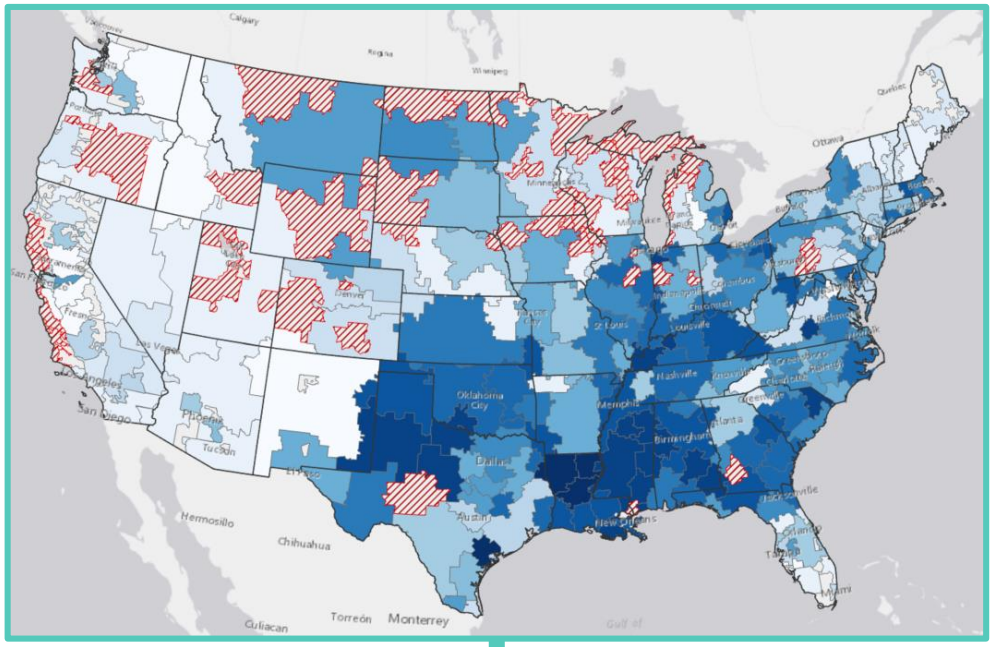
or repeating shapes contained within the same feature class

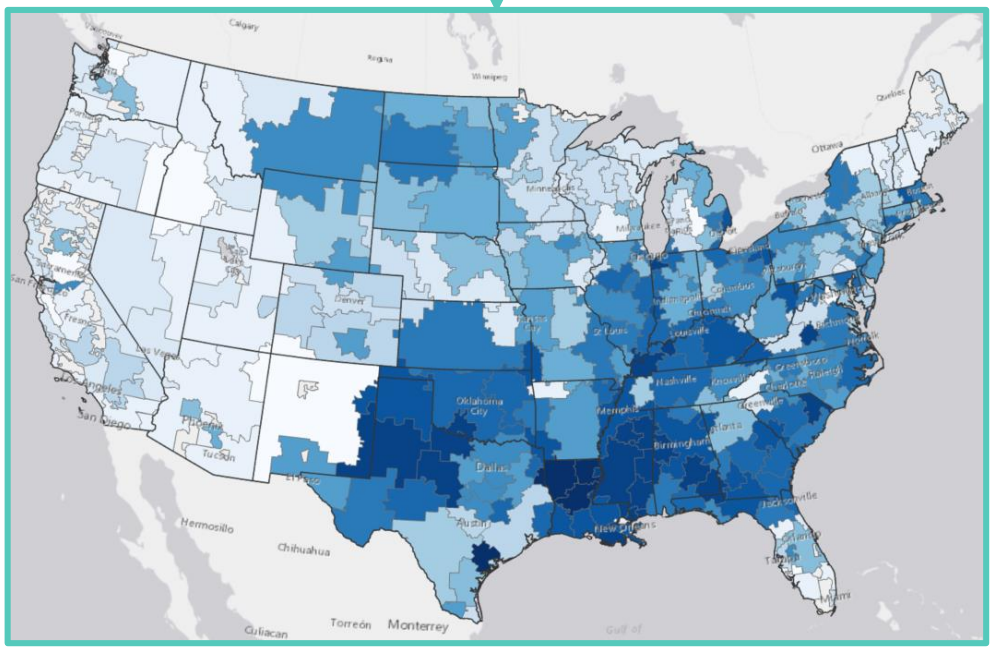
or repeating shapes contained within the same feature class



Fill Missing Values

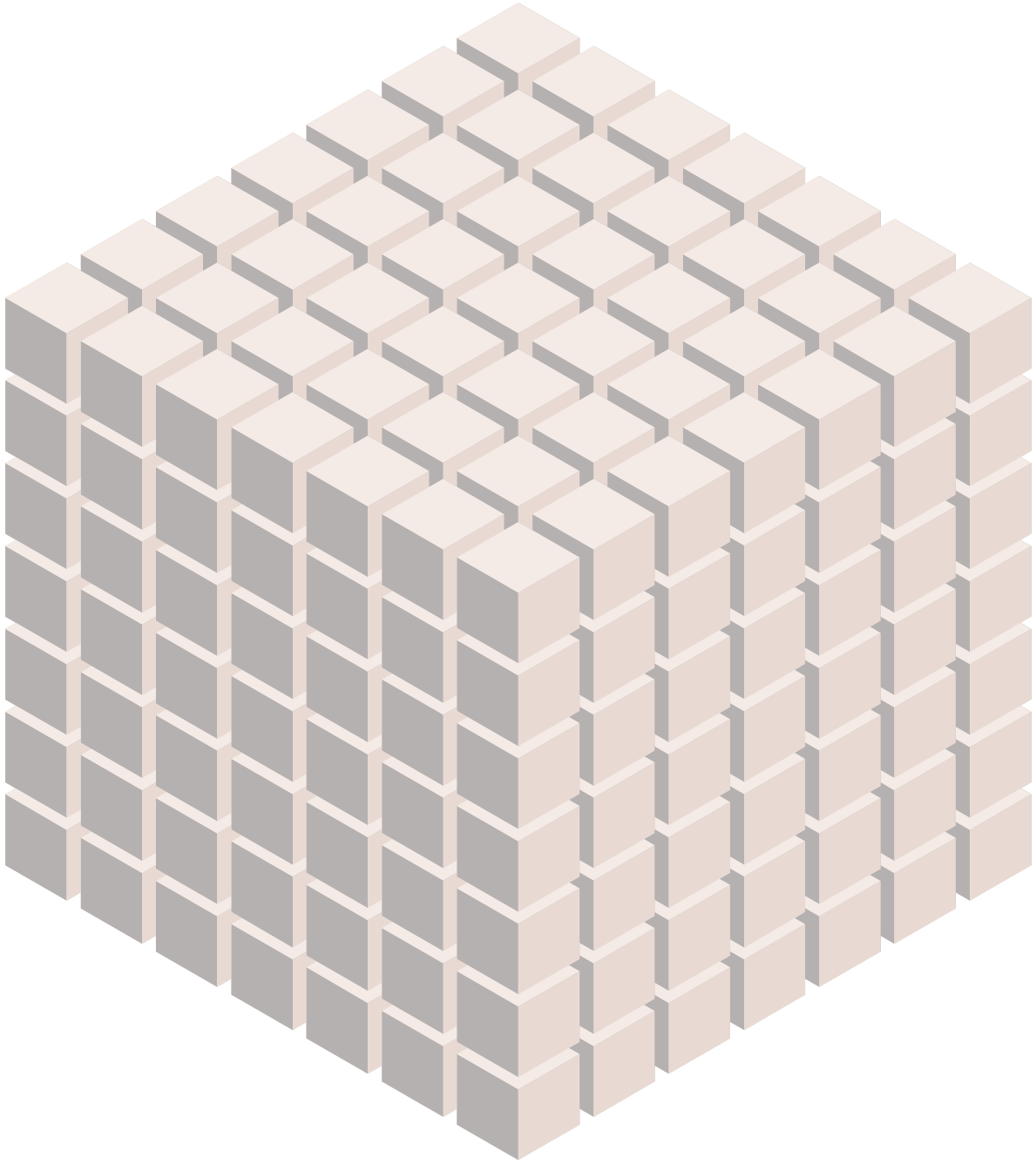
8447.86	1.129	0.1746	176.081215
9576.94	1.146	0.1679	189.160293
6494.61	0.96	0.1291	-99
7792	1.062	0.1667	238.410596
6350.27	0.897	0.1279	-99
6936.38	0.994	0.1482	-99
7200.04	1.037	0.1602	180.940893
7113.31	1.107	0.1742	156.364278
8270.93	1.118	0.1294	-99
9919.04	1.304	0.201	214.627011
10980.52	1.261	0.2125	272.243164
9126.52	1.161	0.1838	279.776179
11150.28	1.236	0.1869	228.033214
6689.43	1.006	0.1433	-99
9633.46	1.233	0.2039	234.204226

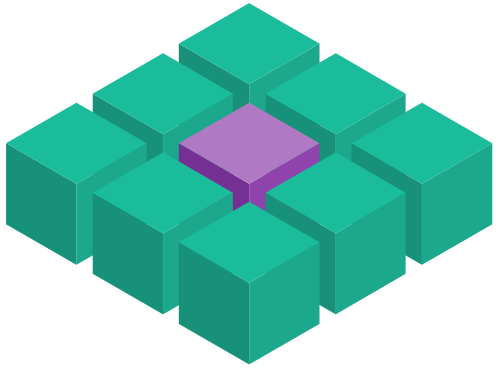


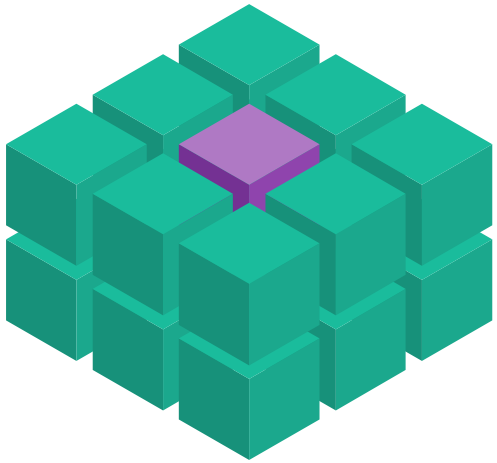


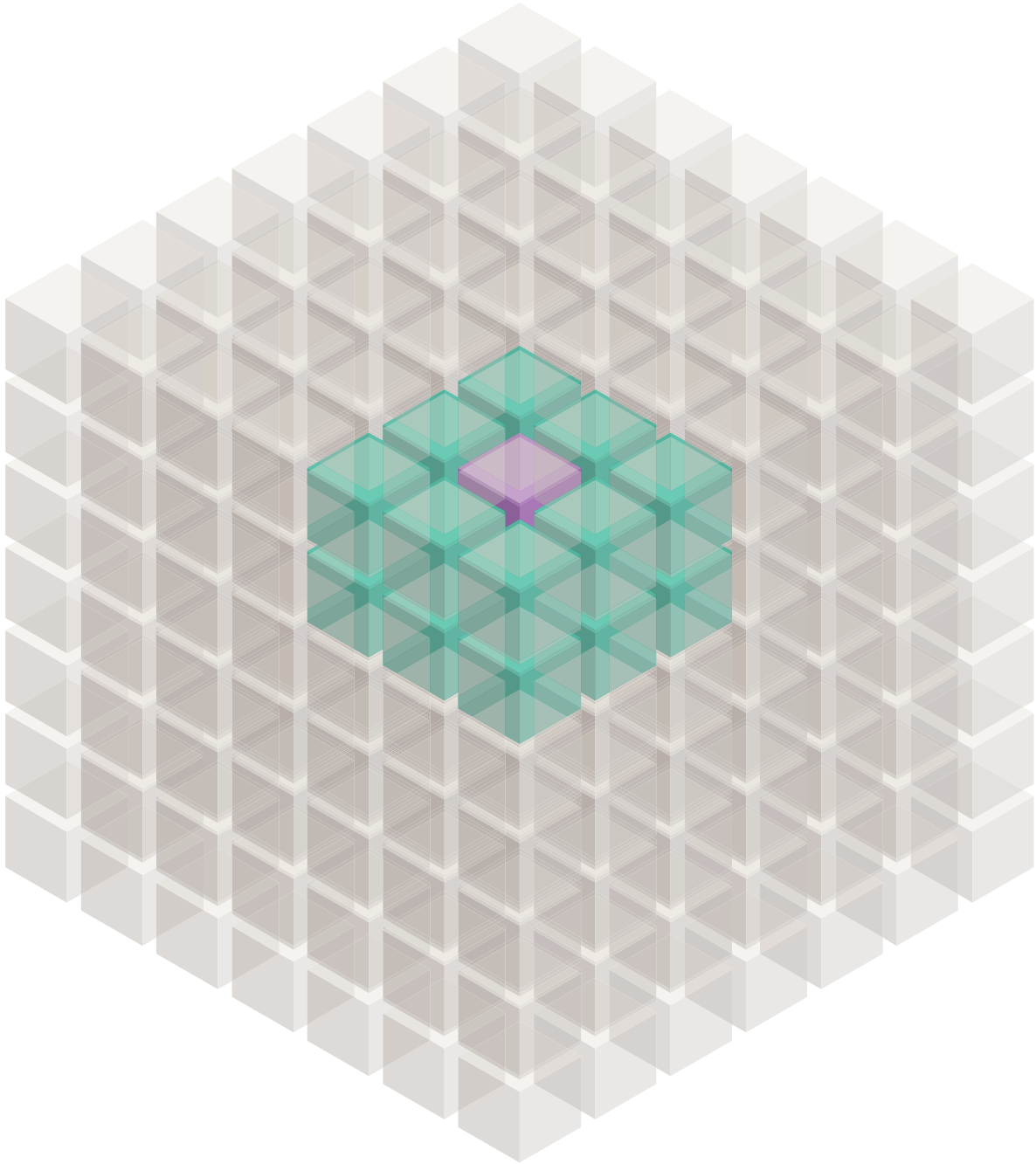
Emerging Hot Spot Analysis

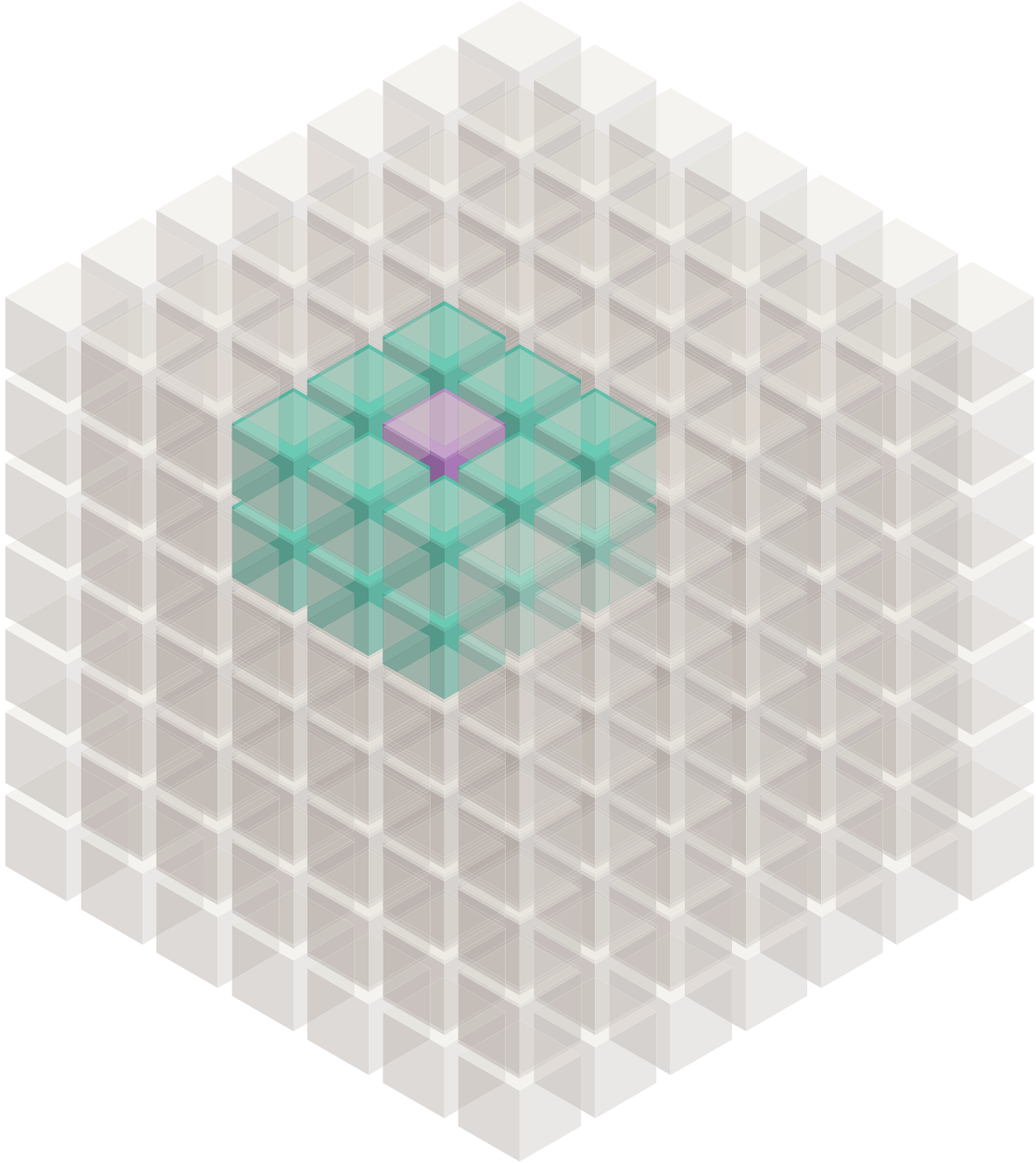
identifies trends in the clustering of counts or summary fields in a space time cube

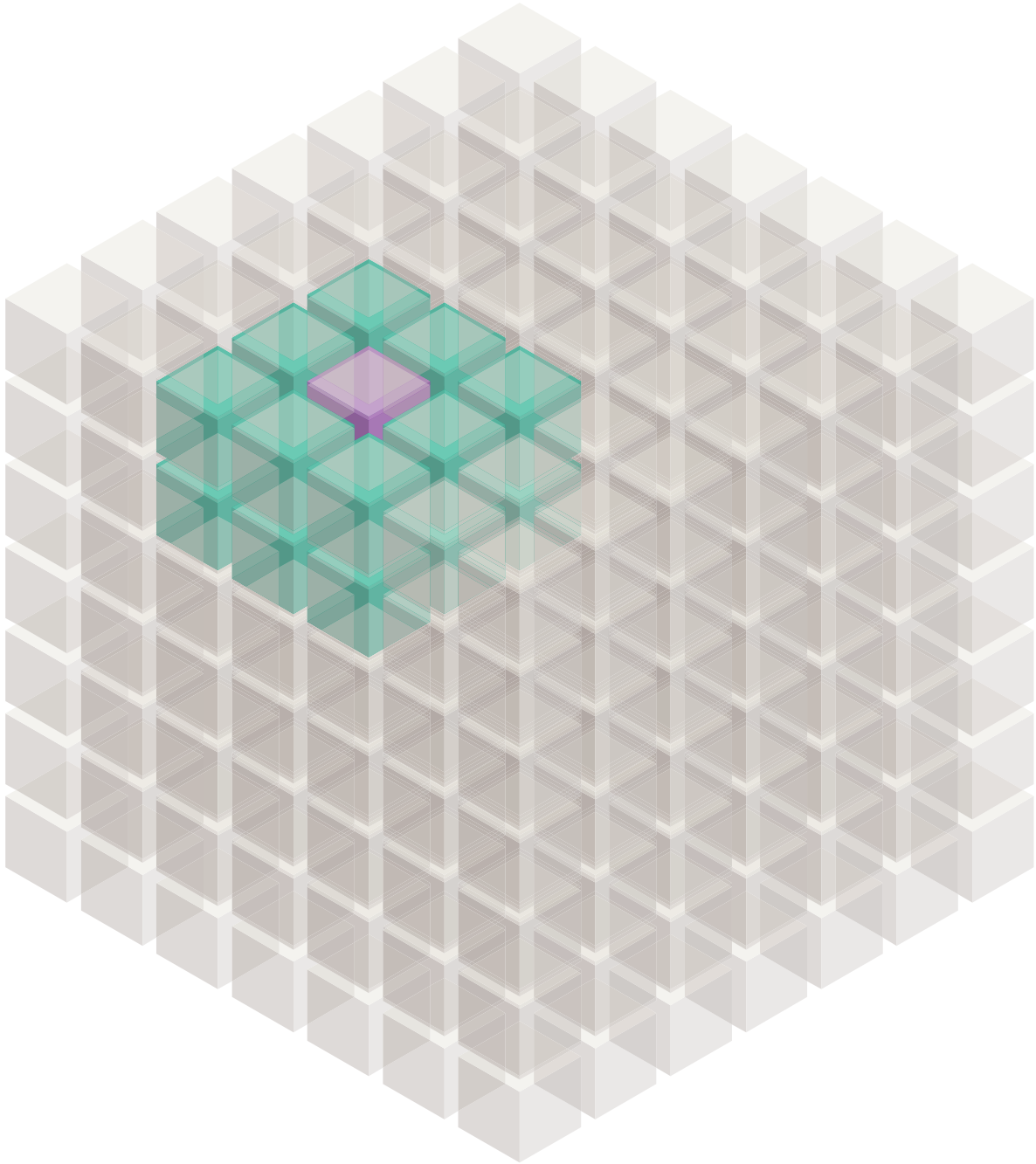




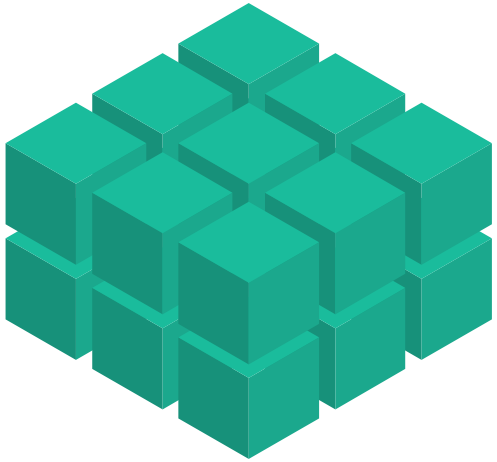


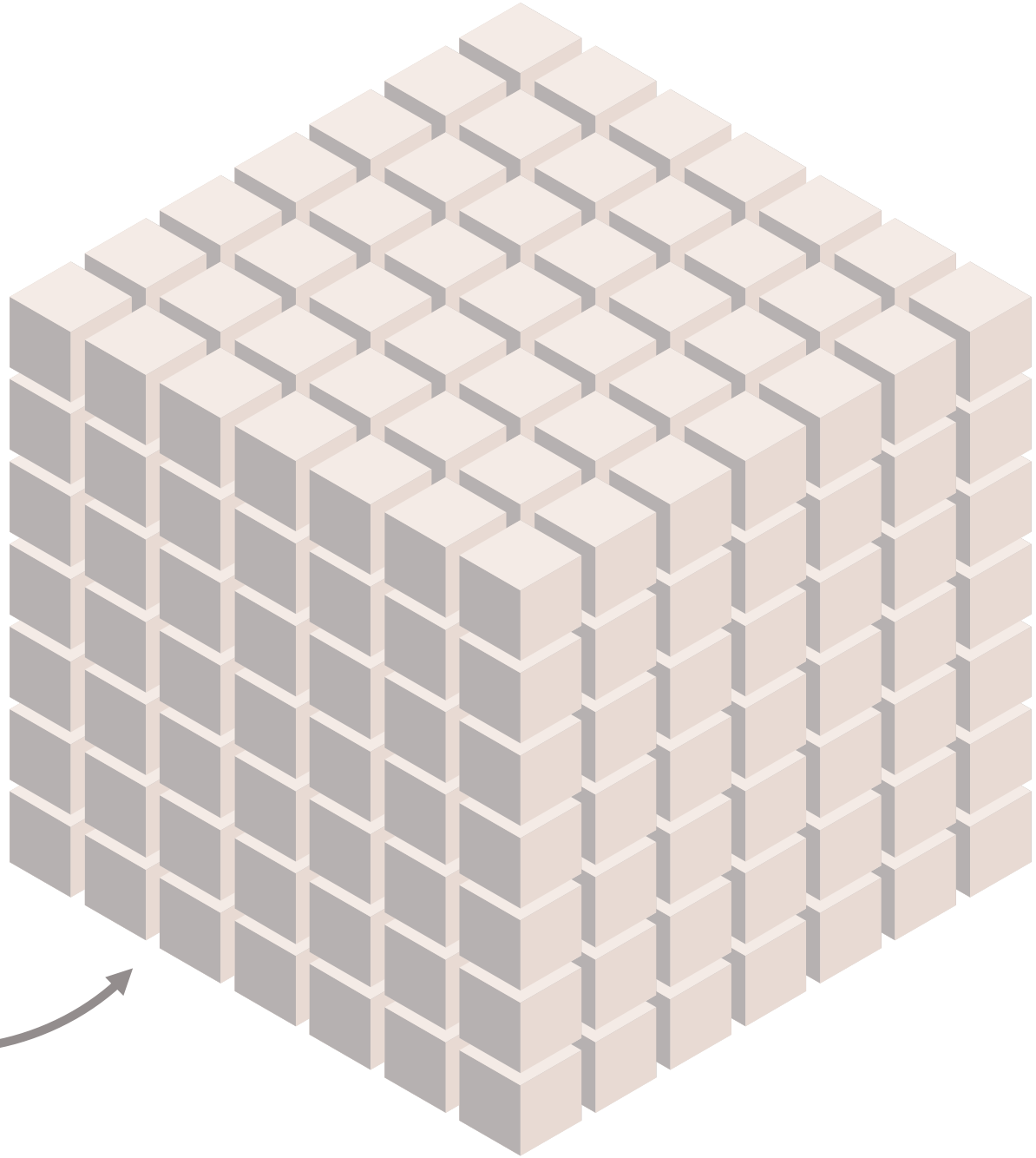






is this

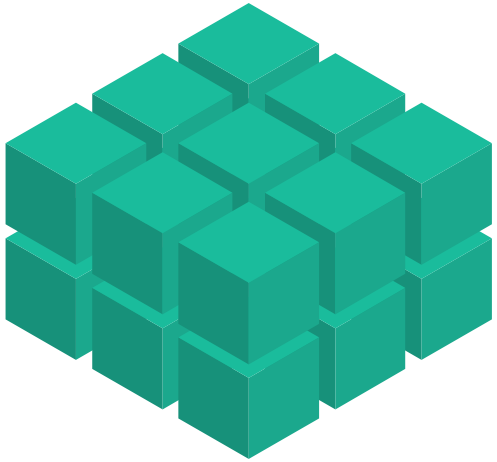


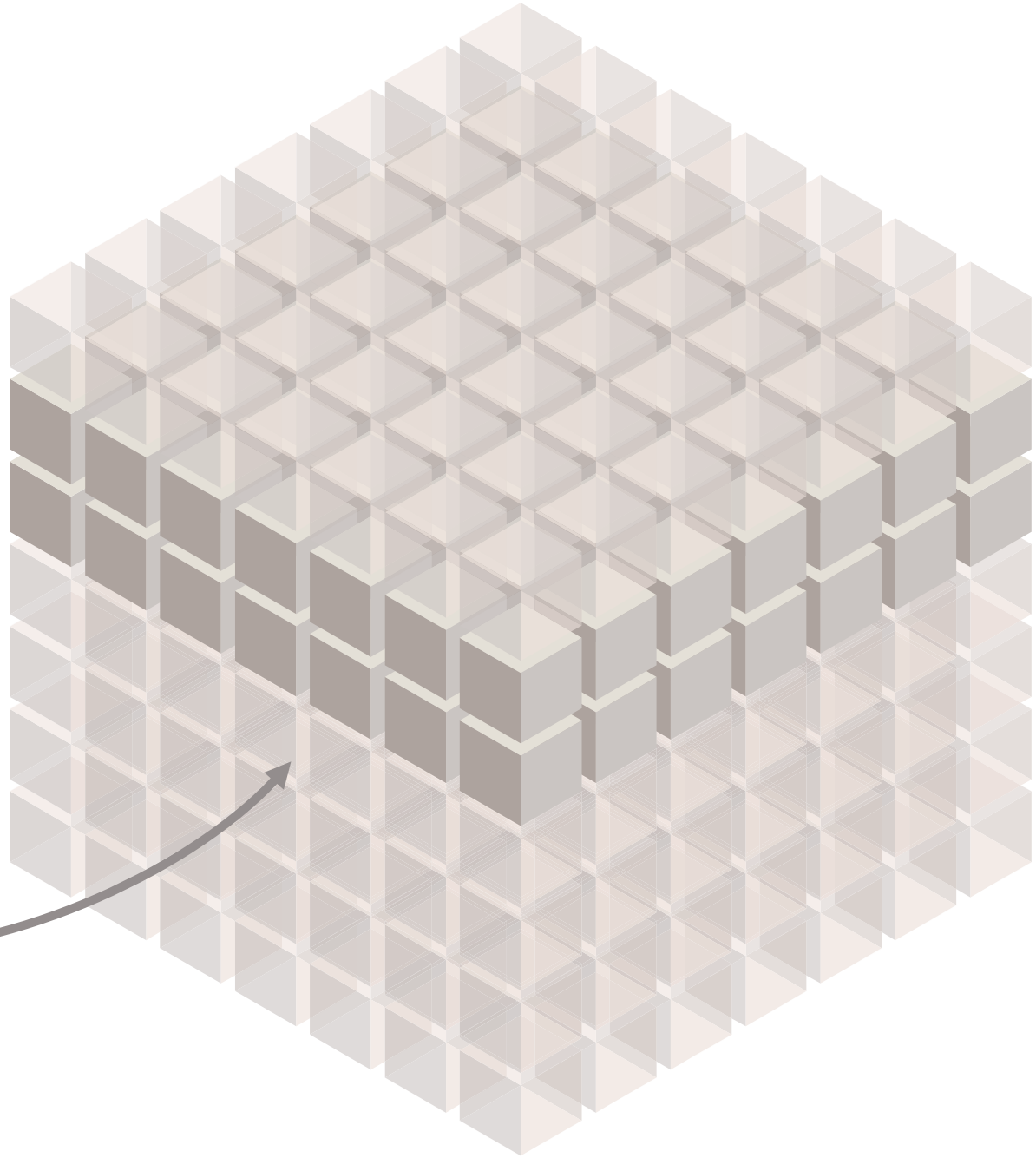


significantly
different from this?

Entire Cube

is this

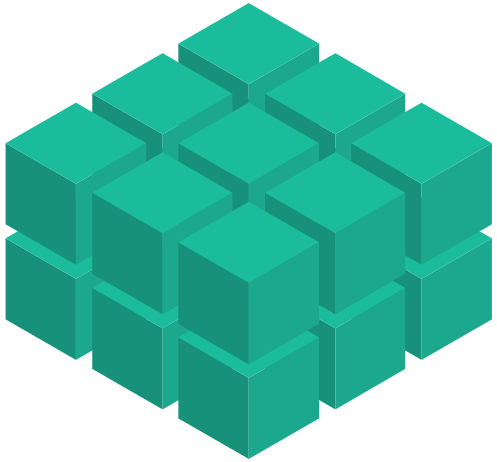


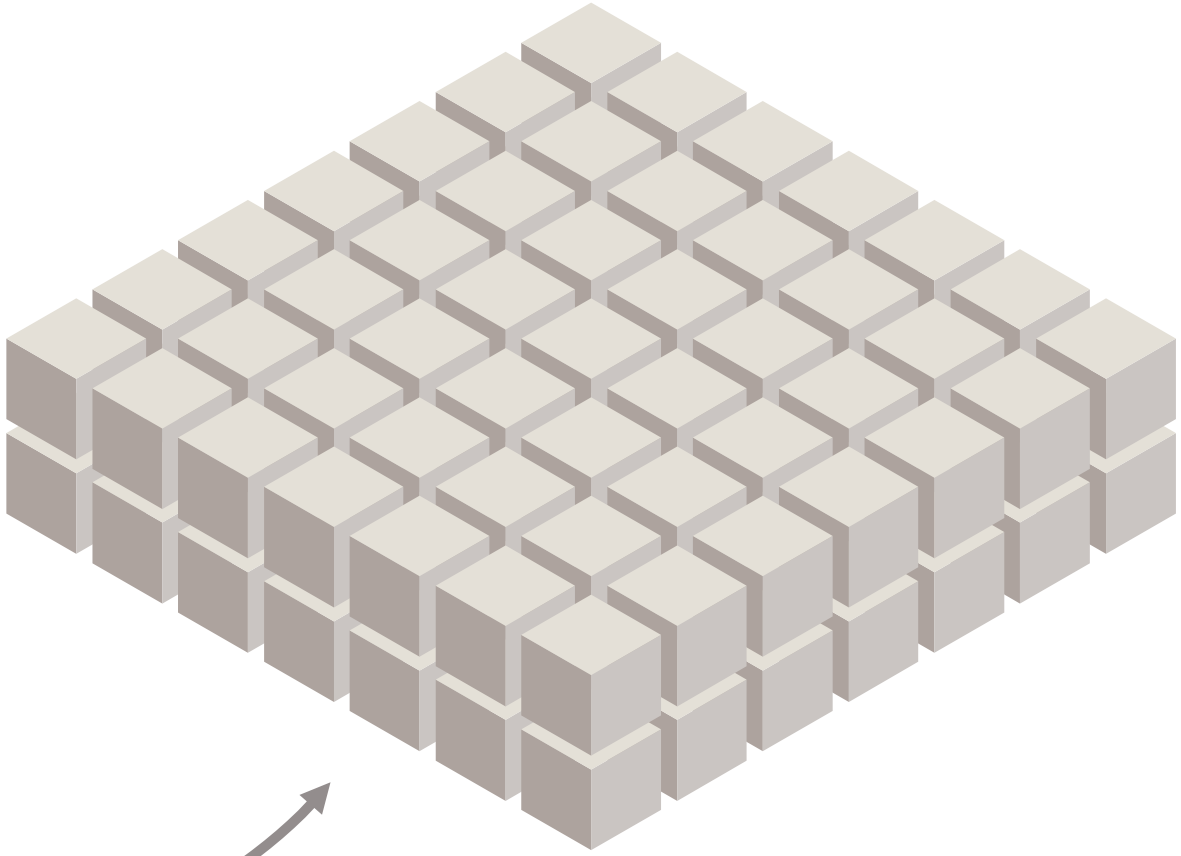


significantly
different from this?

Neighborhood Time Step

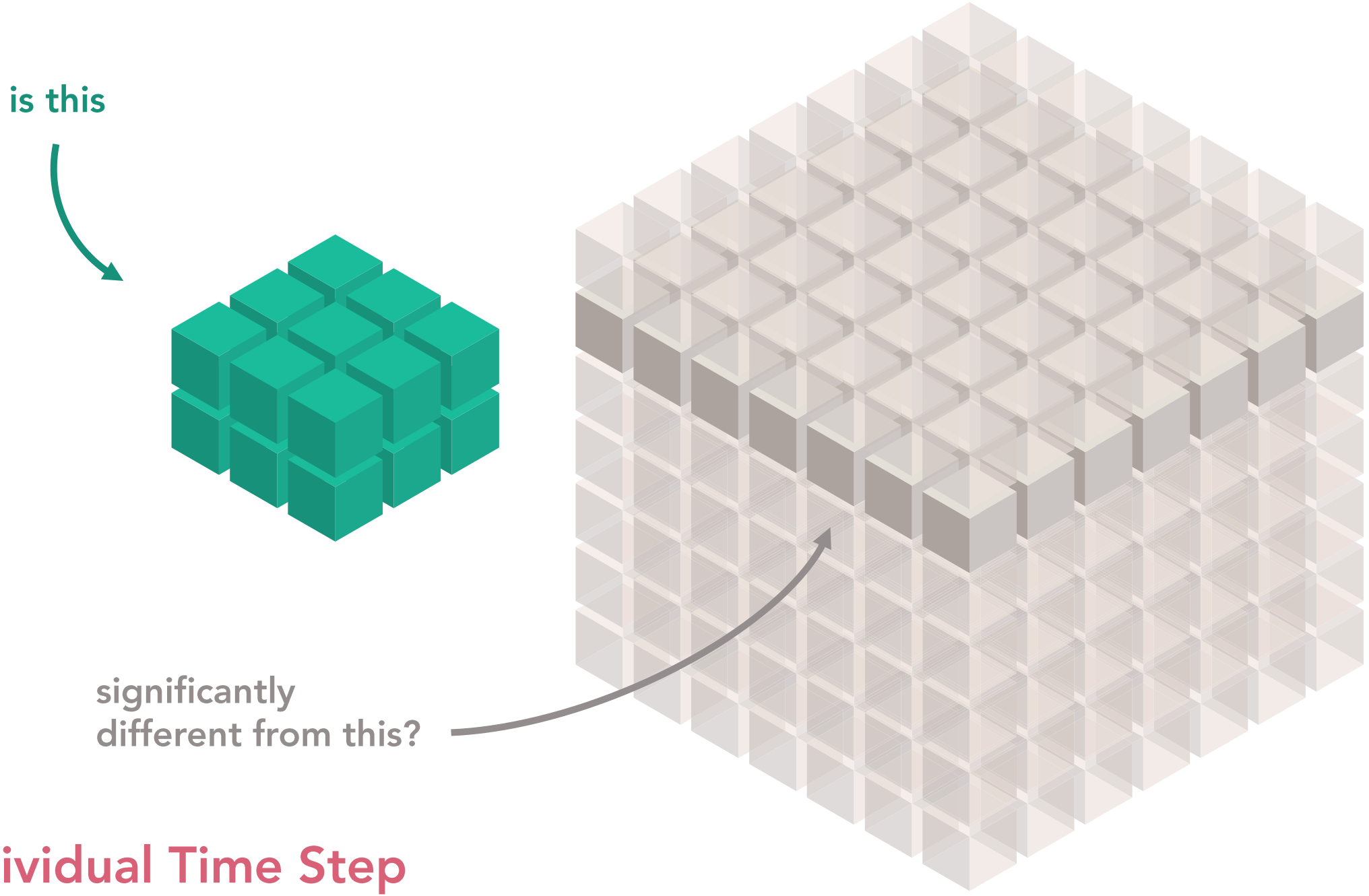
is this





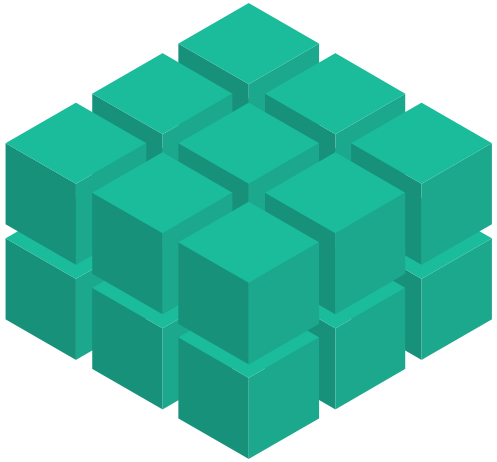
significantly
different from this?

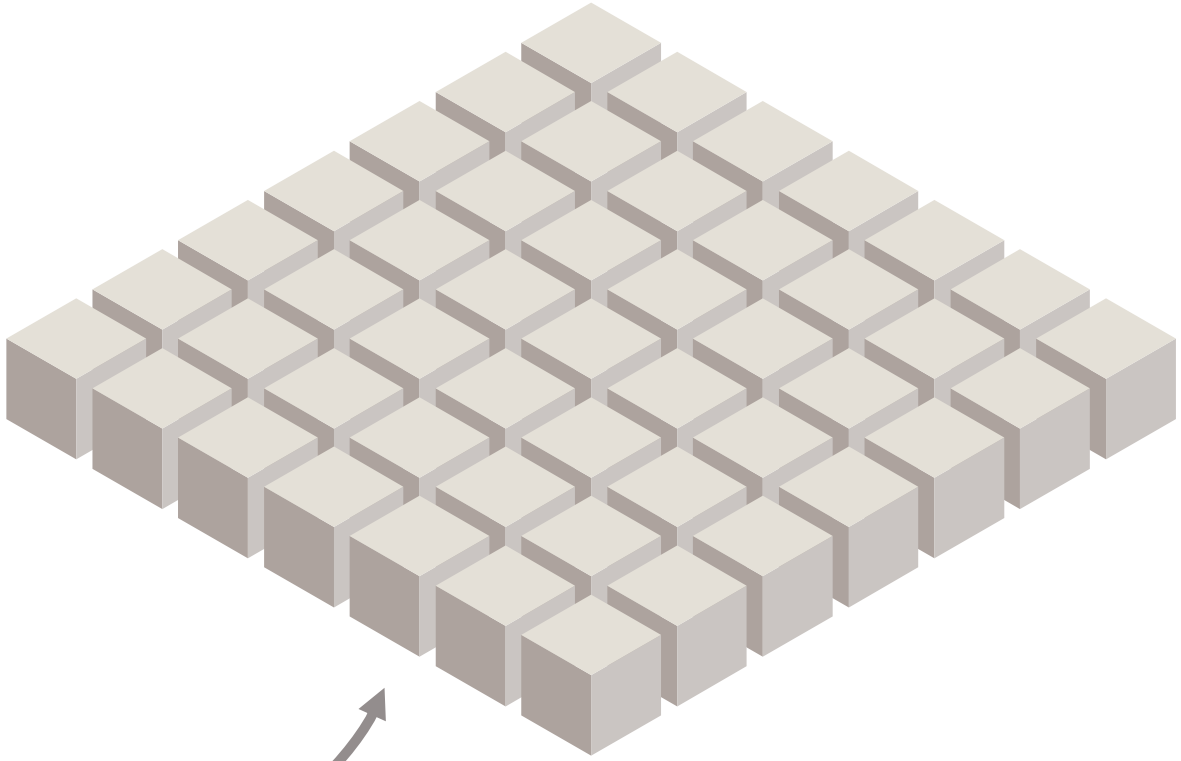
Neighborhood Time Step



Individual Time Step

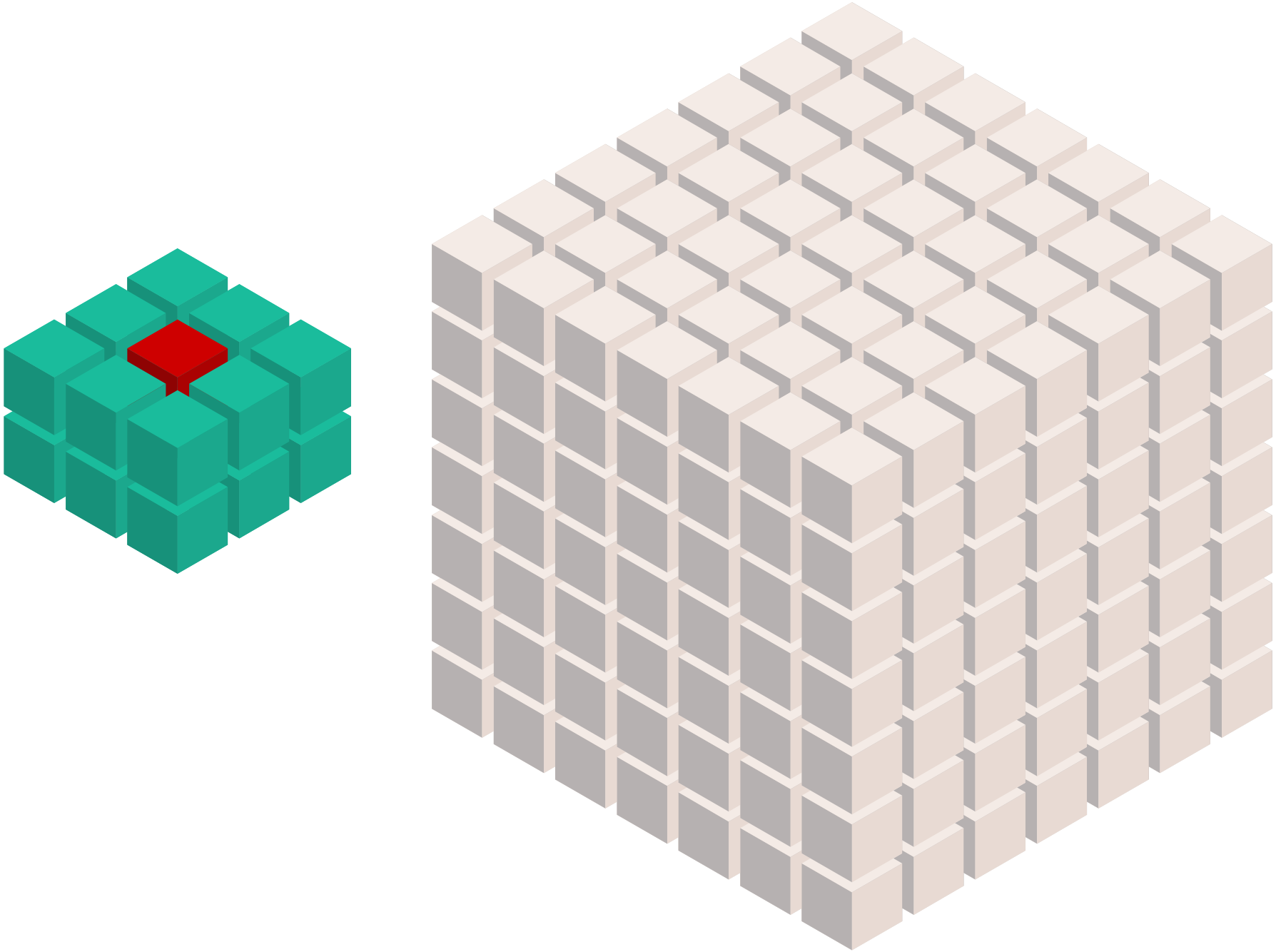
is this

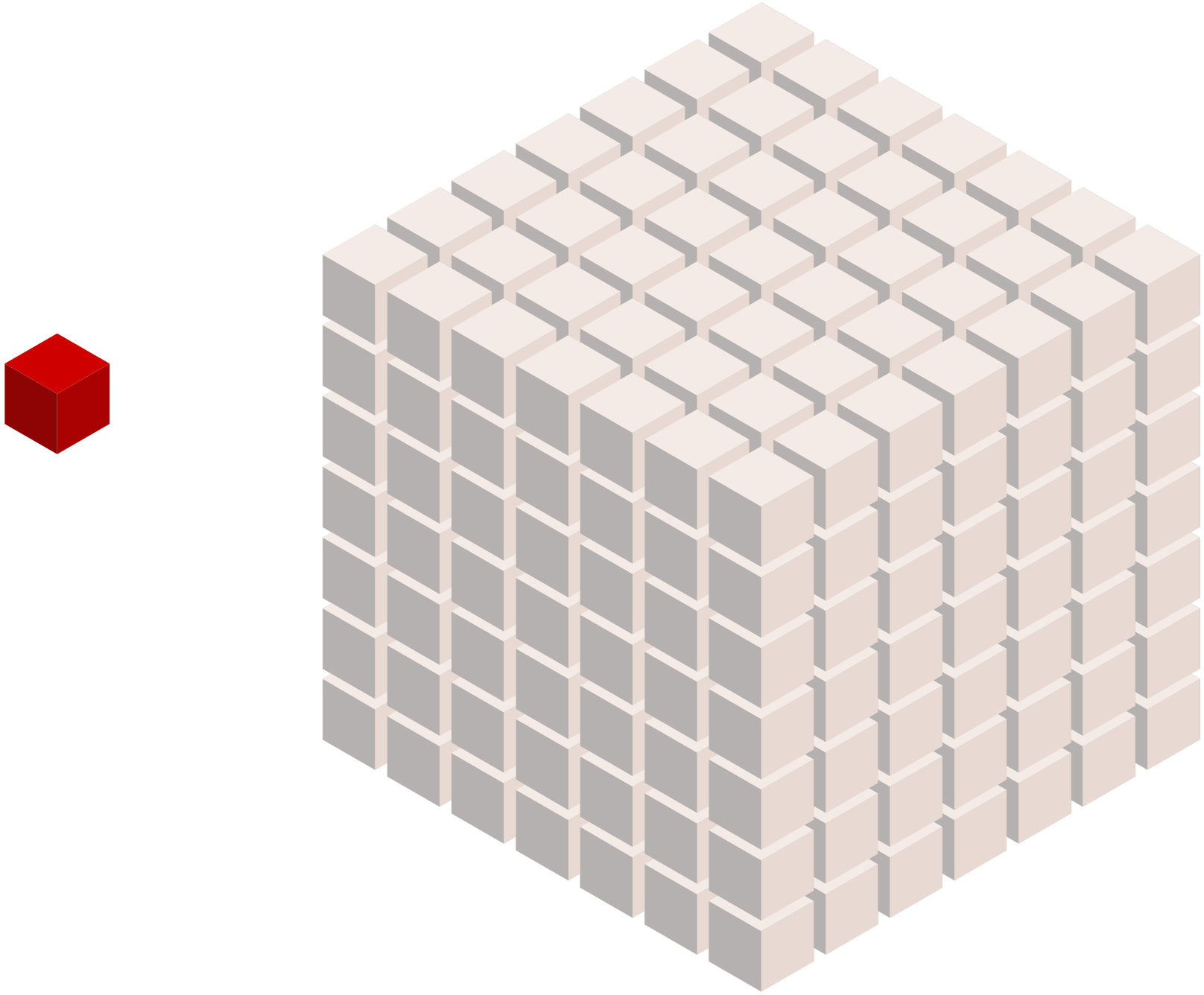


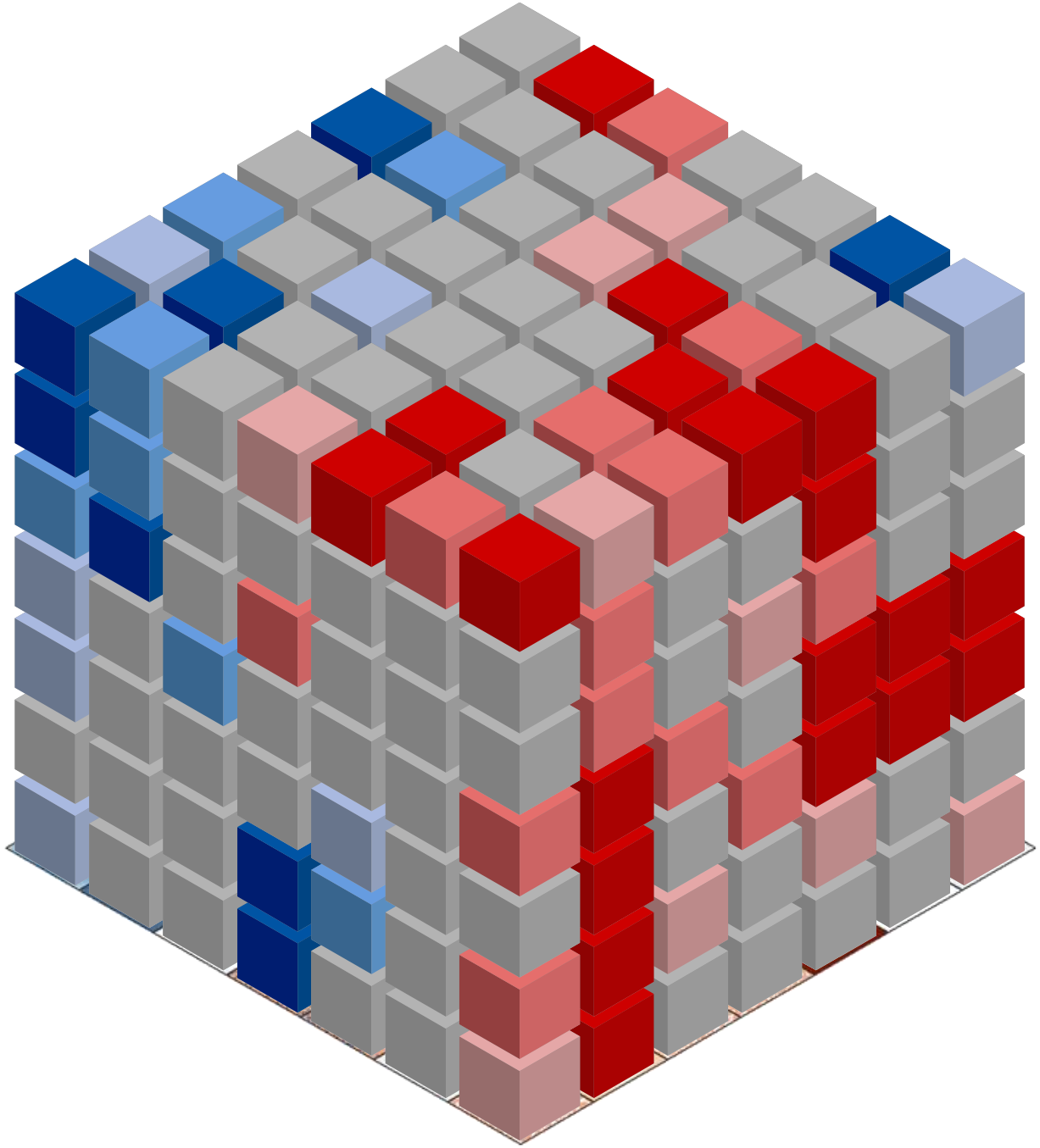


significantly
different from this?

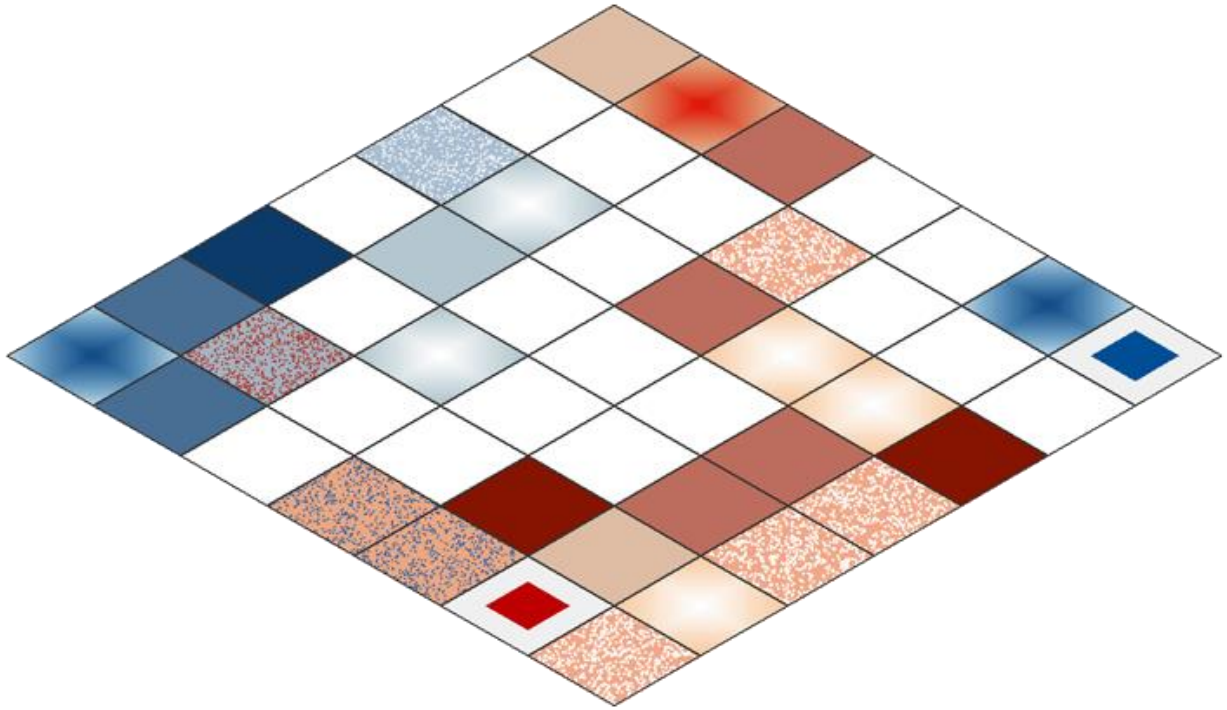
Individual Time Step

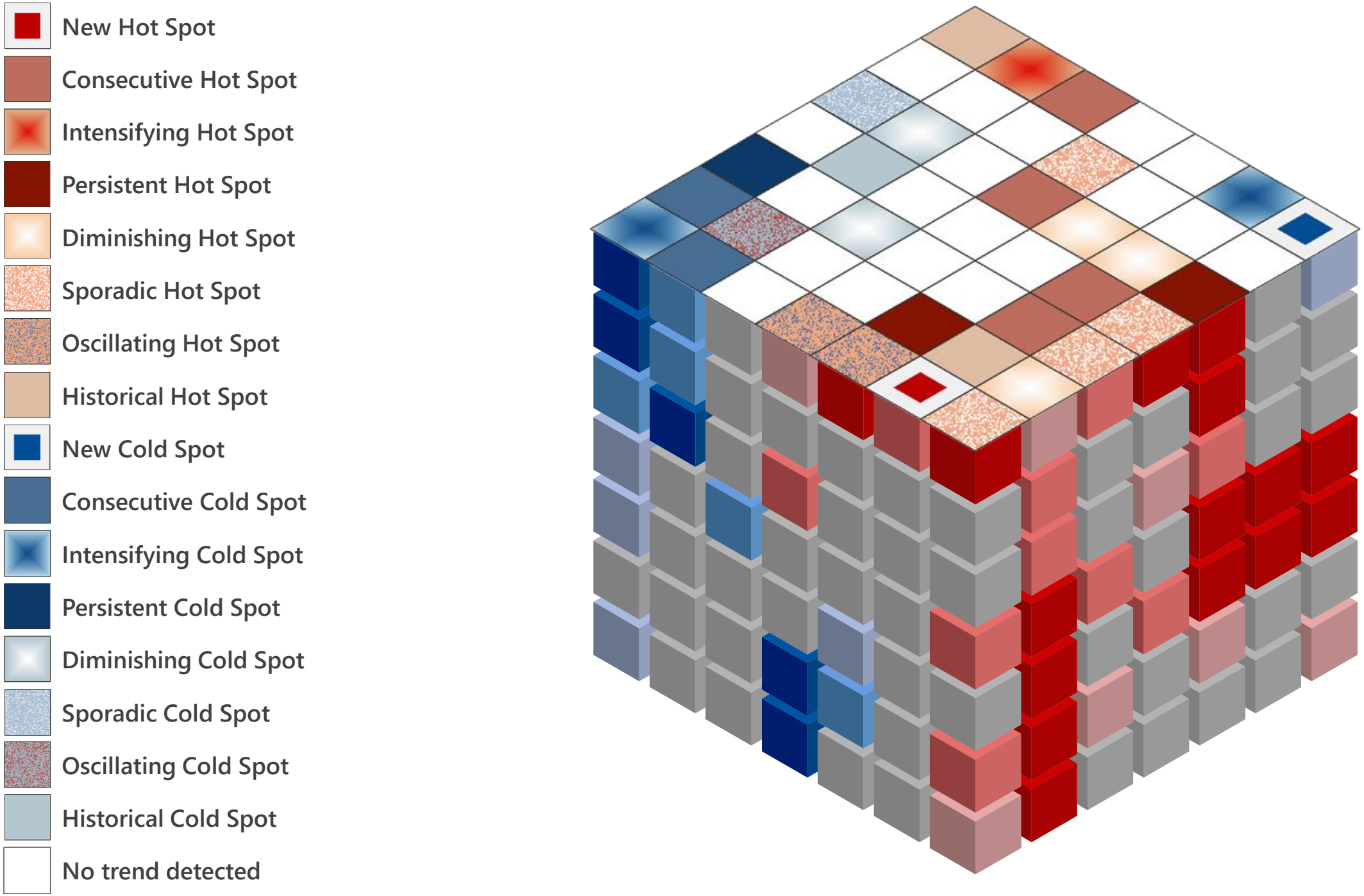


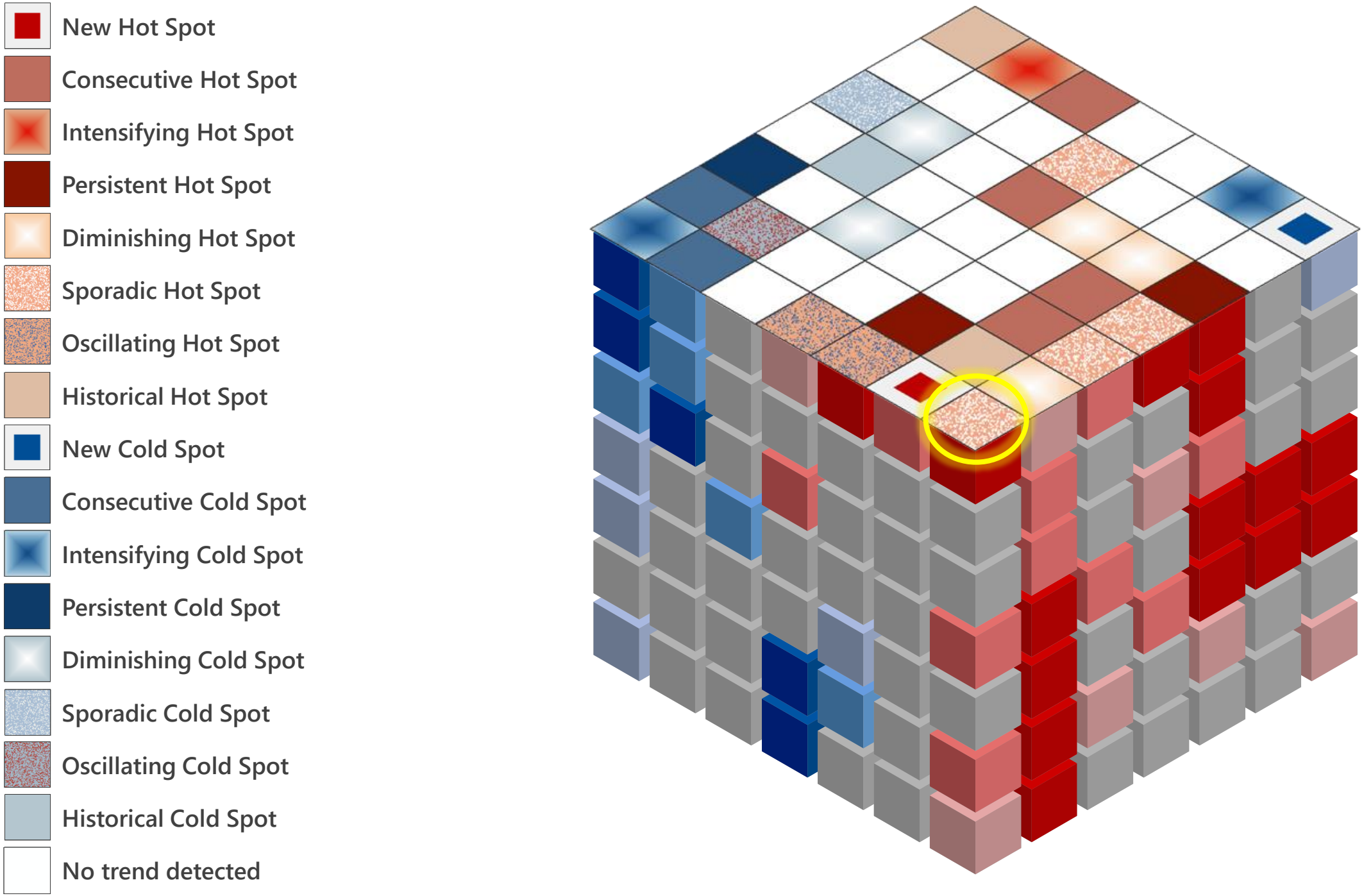




- New Hot Spot
- Consecutive Hot Spot
- Intensifying Hot Spot
- Persistent Hot Spot
- Diminishing Hot Spot
- Sporadic Hot Spot
- Oscillating Hot Spot
- Historical Hot Spot
- New Cold Spot
- Consecutive Cold Spot
- Intensifying Cold Spot
- Persistent Cold Spot
- Diminishing Cold Spot
- Sporadic Cold Spot
- Oscillating Cold Spot
- Historical Cold Spot
- No trend detected




New Hot Spot
Consecutive Hot Spot
Intensifying Hot Spot
Persistent Hot Spot
Diminishing Hot Spot
Sporadic Hot Spot
Oscillating Hot Spot
Historical Hot Spot
New Cold Spot
Consecutive Cold Spot
Intensifying Cold Spot
Persistent Cold Spot
Diminishing Cold Spot
Sporadic Cold Spot
Oscillating Cold Spot
Historical Cold Spot
No trend detected


New Hot Spot
Consecutive Hot Spot
Intensifying Hot Spot
Persistent Hot Spot
Diminishing Hot Spot
Sporadic Hot Spot
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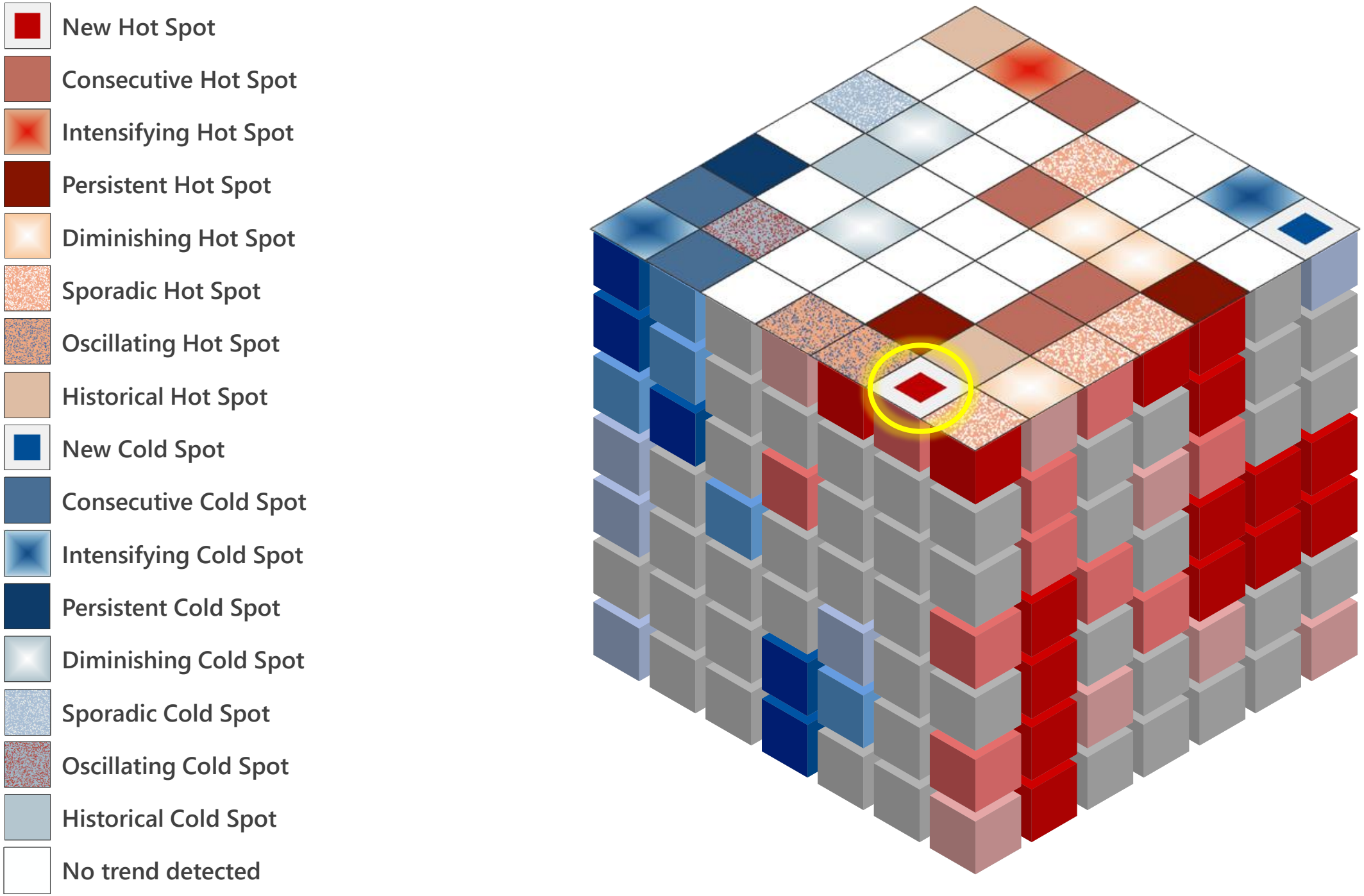
Consecutive Cold Spot
Intensifying Cold Spot
Persistent Cold Spot
Diminishing Cold Spot
Sporadic Cold Spot
Oscillating Cold Spot
Historical Cold Spot
No trend detected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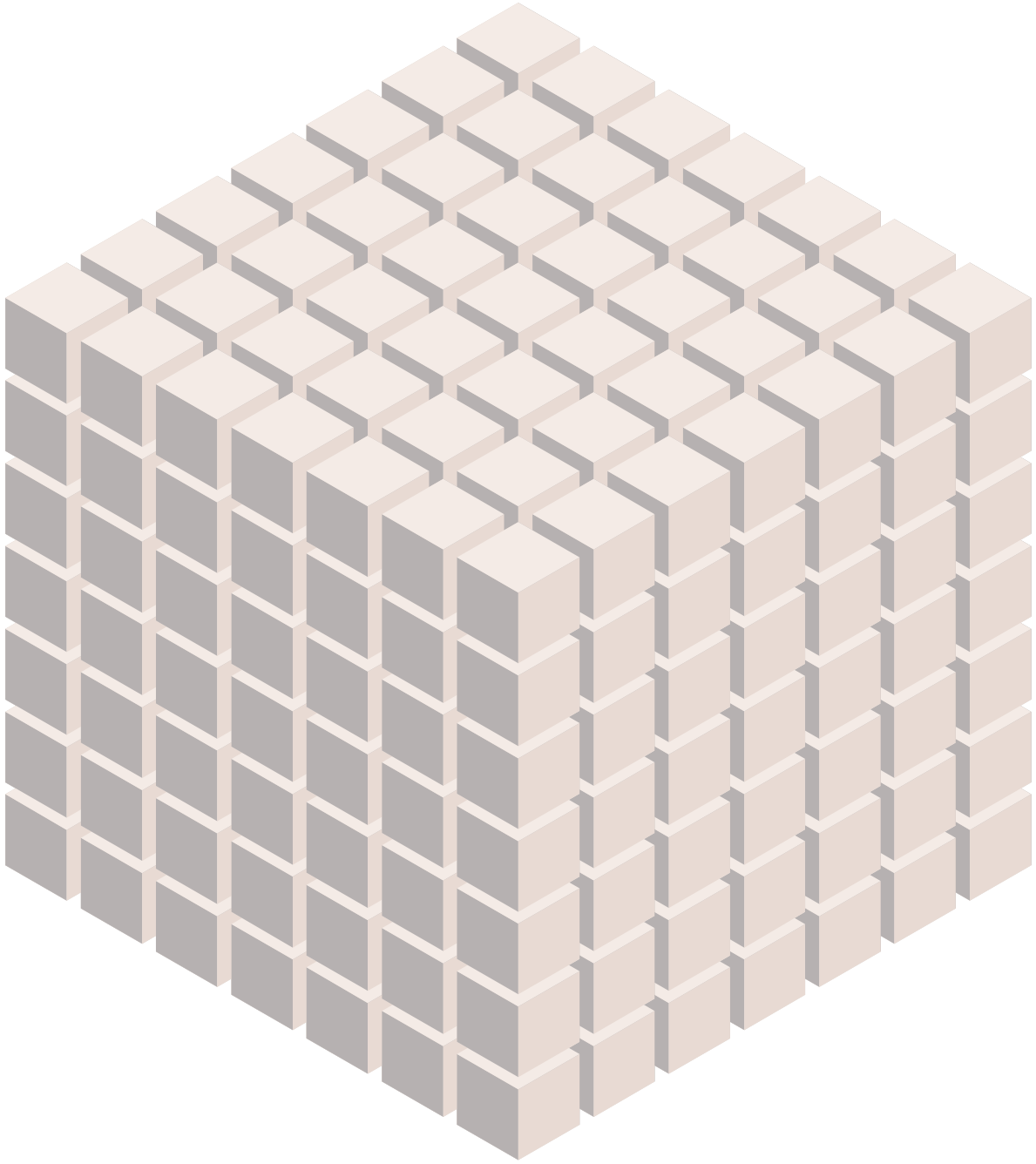
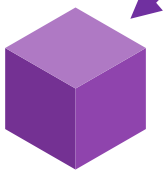
Historical Hot Spot
New Cold Spot
Consecutive Cold Spot
Intensifying Cold Spot
Persistent Cold Spot
Diminishing Cold Spot
Sporadic Cold Spot
Oscillating Cold Spot
Historical Cold Spot
No trend detected

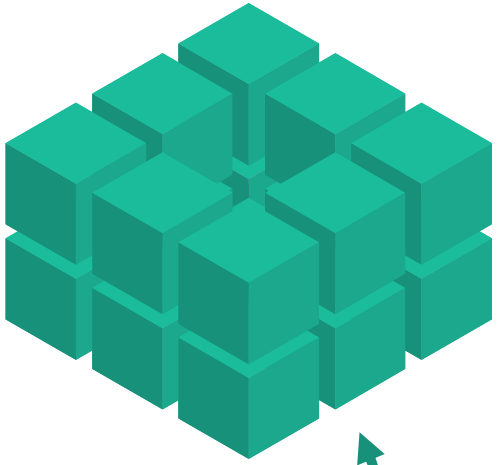
Local Outlier Analysis

identifies statistically significant clusters and outliers in the context of both space and time

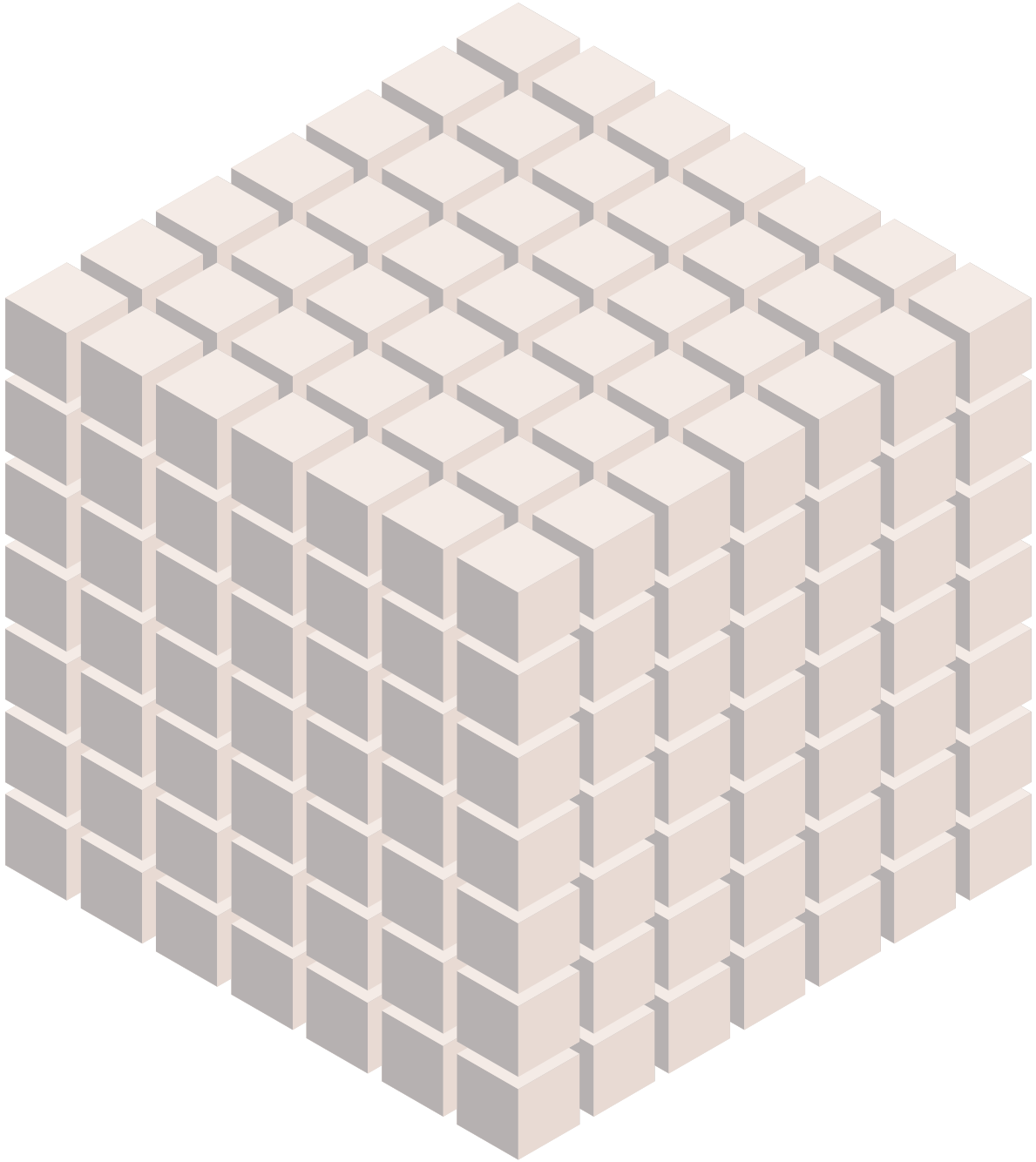


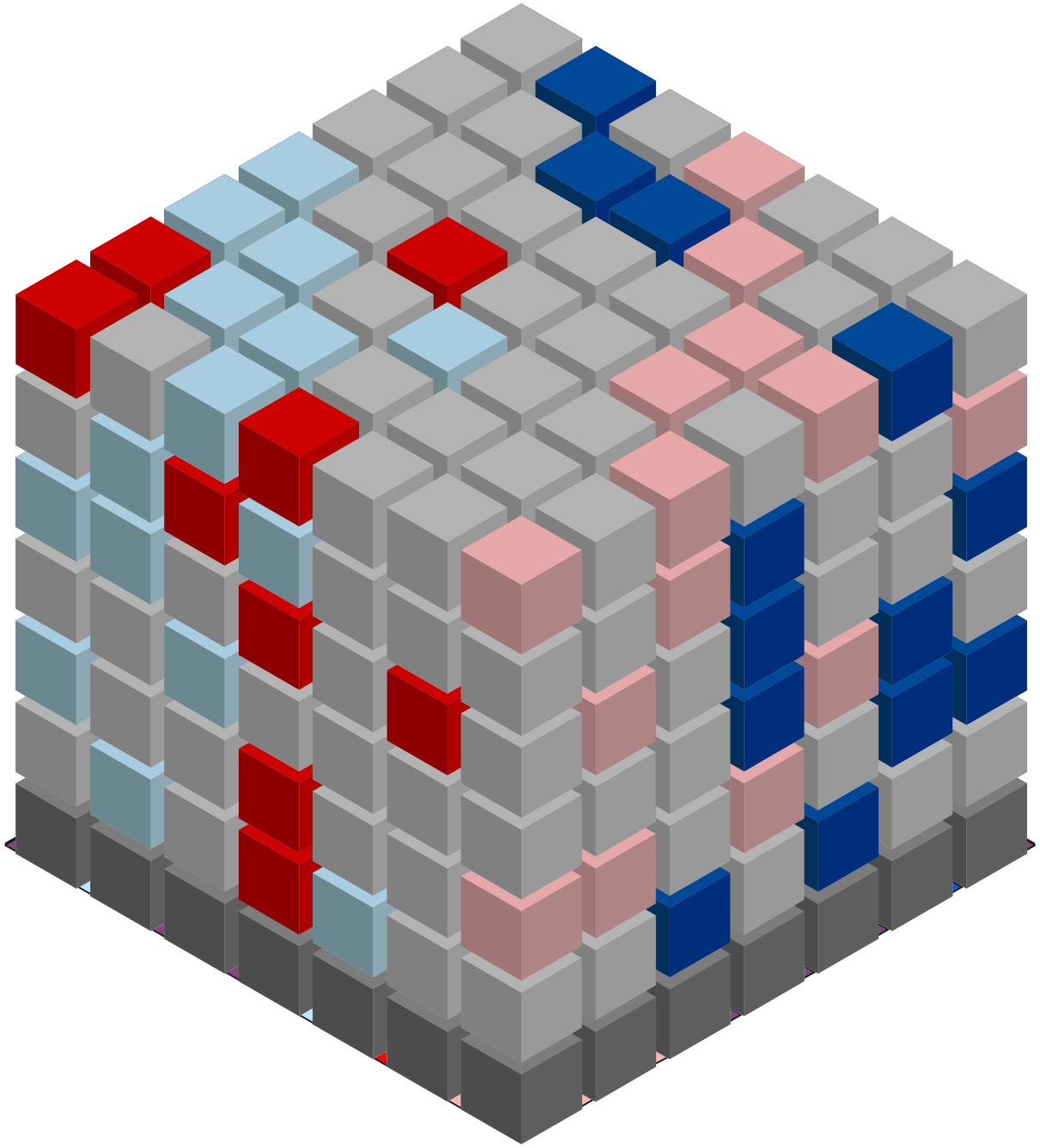
is the bin significantly different from all other bins?

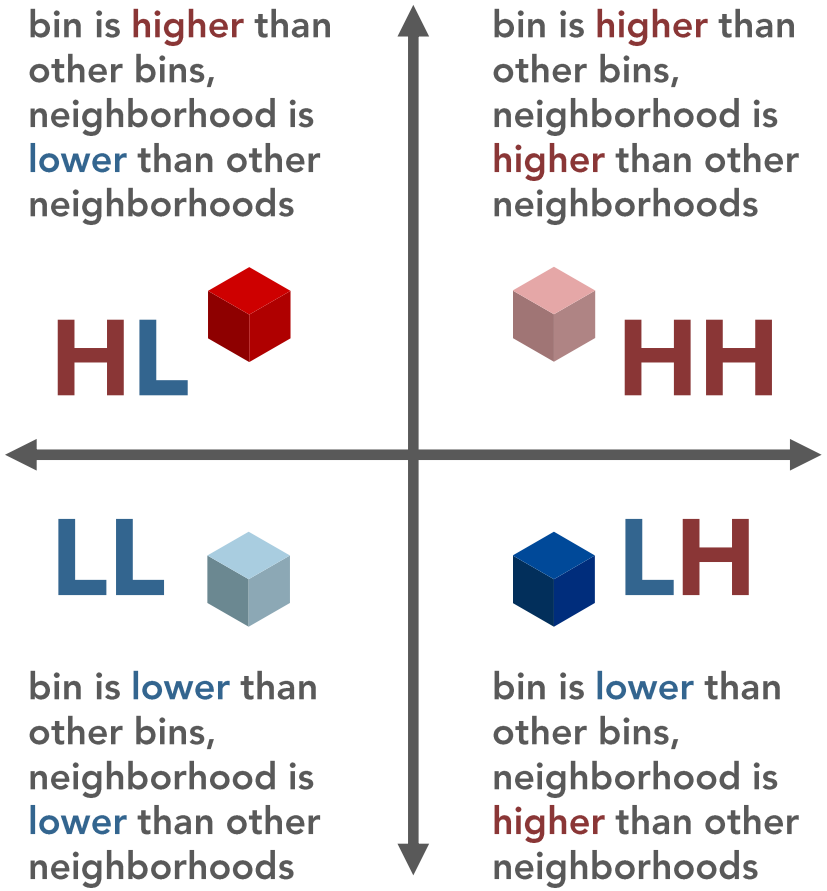


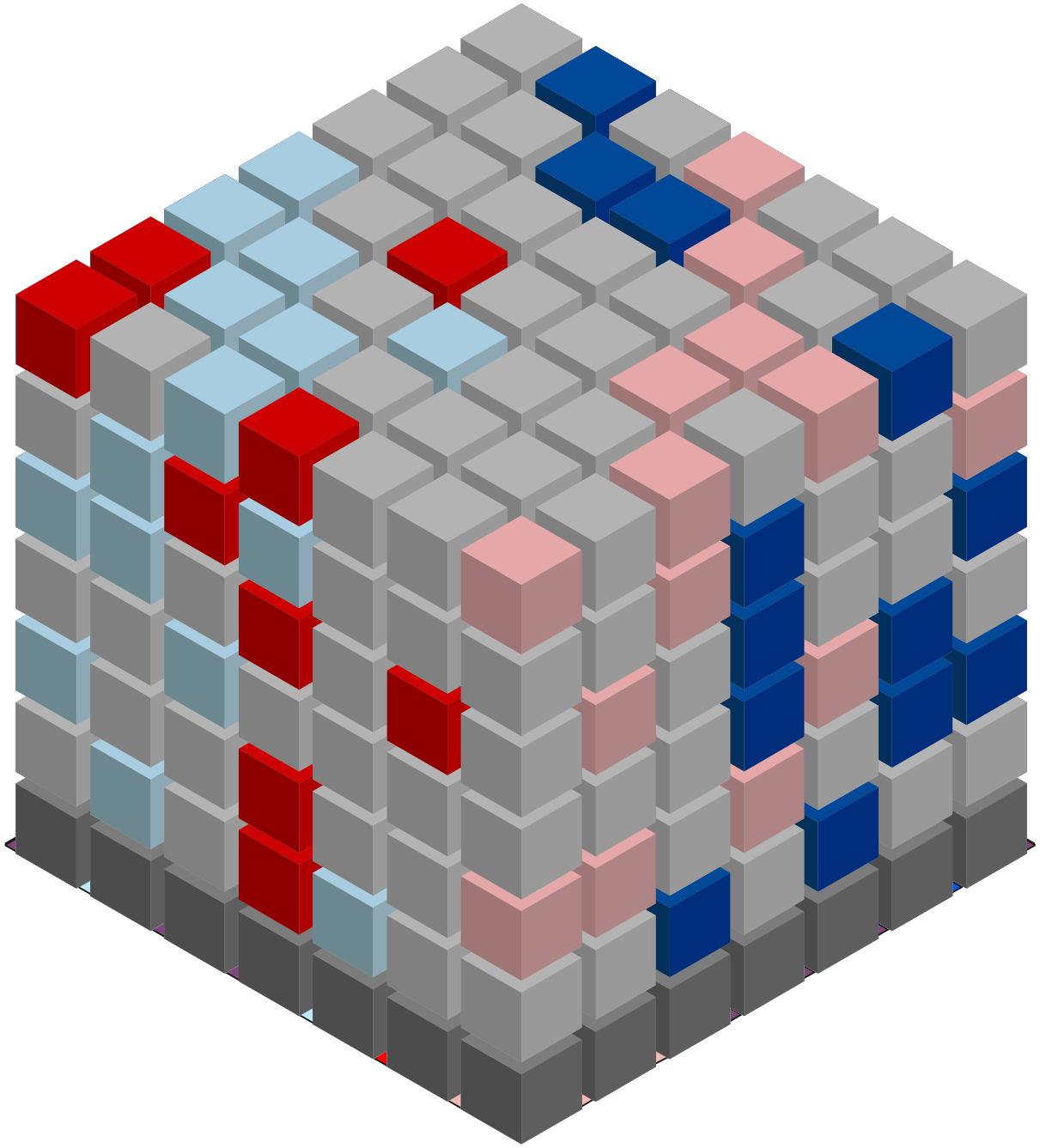


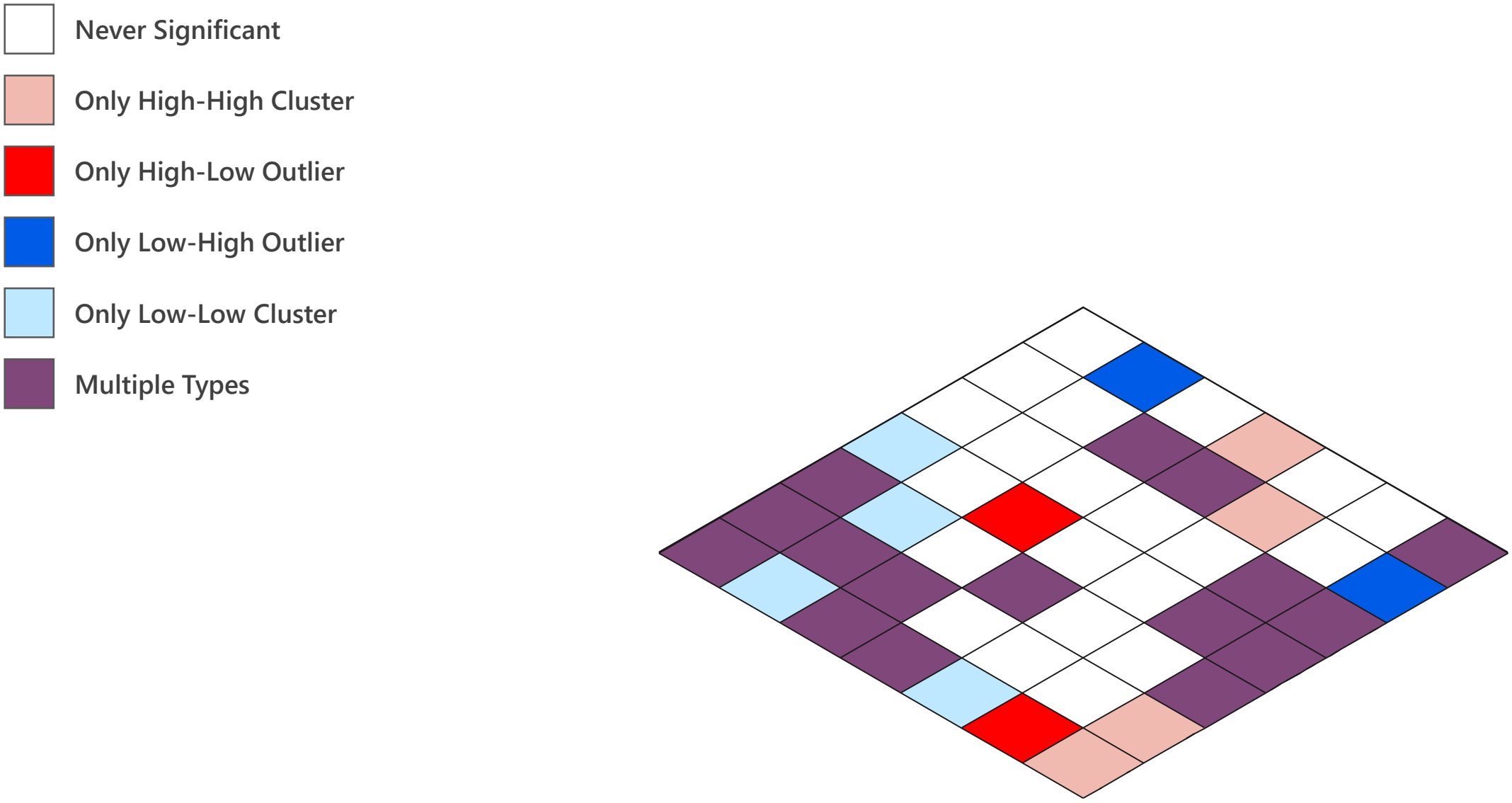
is the neighborhood significantly different from all other neighborhoods?

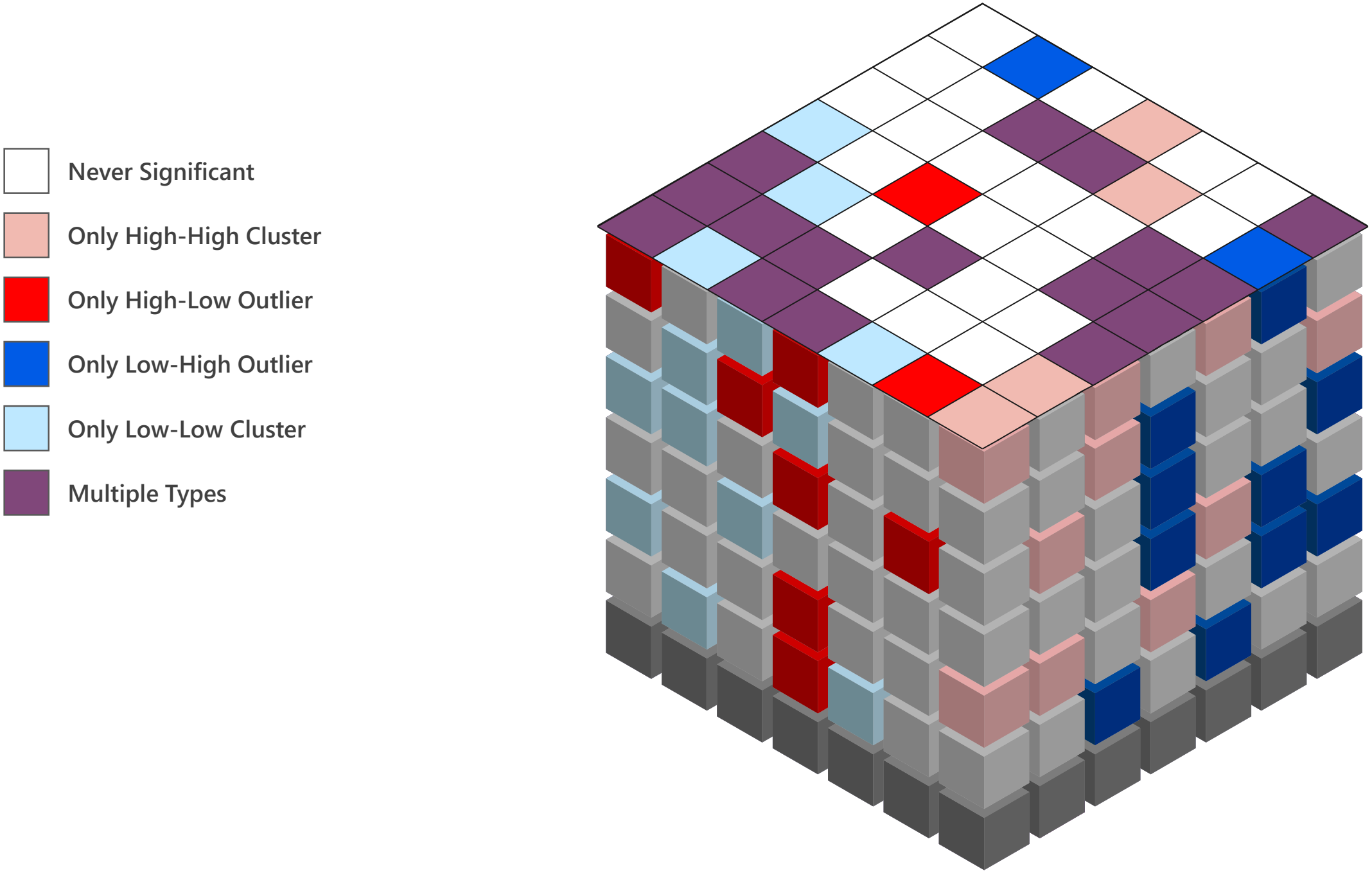





bin is higher than other bins, neighborhood is lower than other neighborhoods
HL
bin is higher than other bins, neighborhood is higher than other neighborhoods
HH
LL
bin is lower than other bins, neighborhood is lower than other neighborhoods
LH
bin is lower than other bins, neighborhood is higher than other neighborhoods




Never Significant
Only High-High Cluster
Only High-Low Outlier
Only Low-High Outlier
Only Low-Low Cluster
Multiple Types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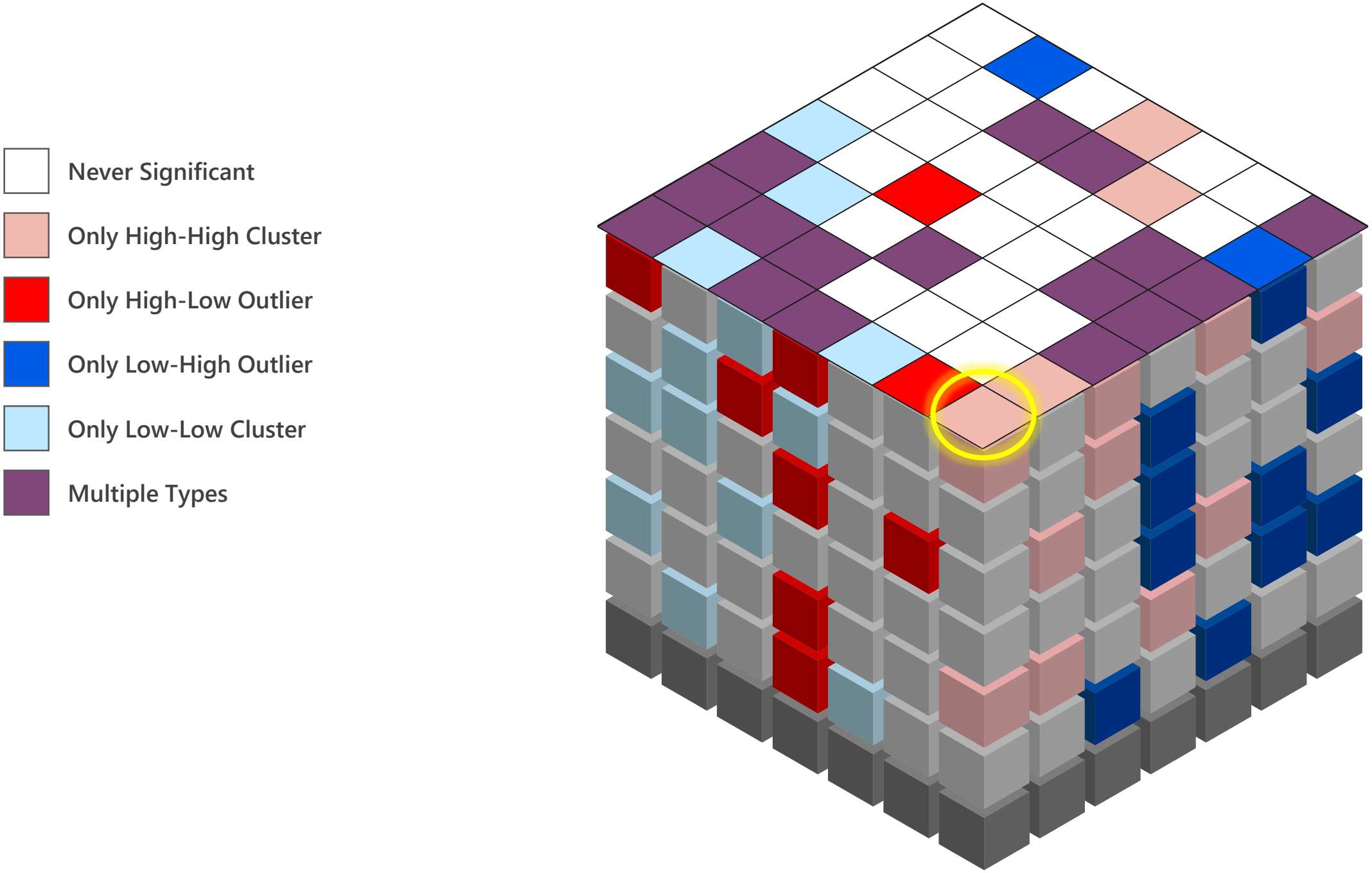
Multiple Types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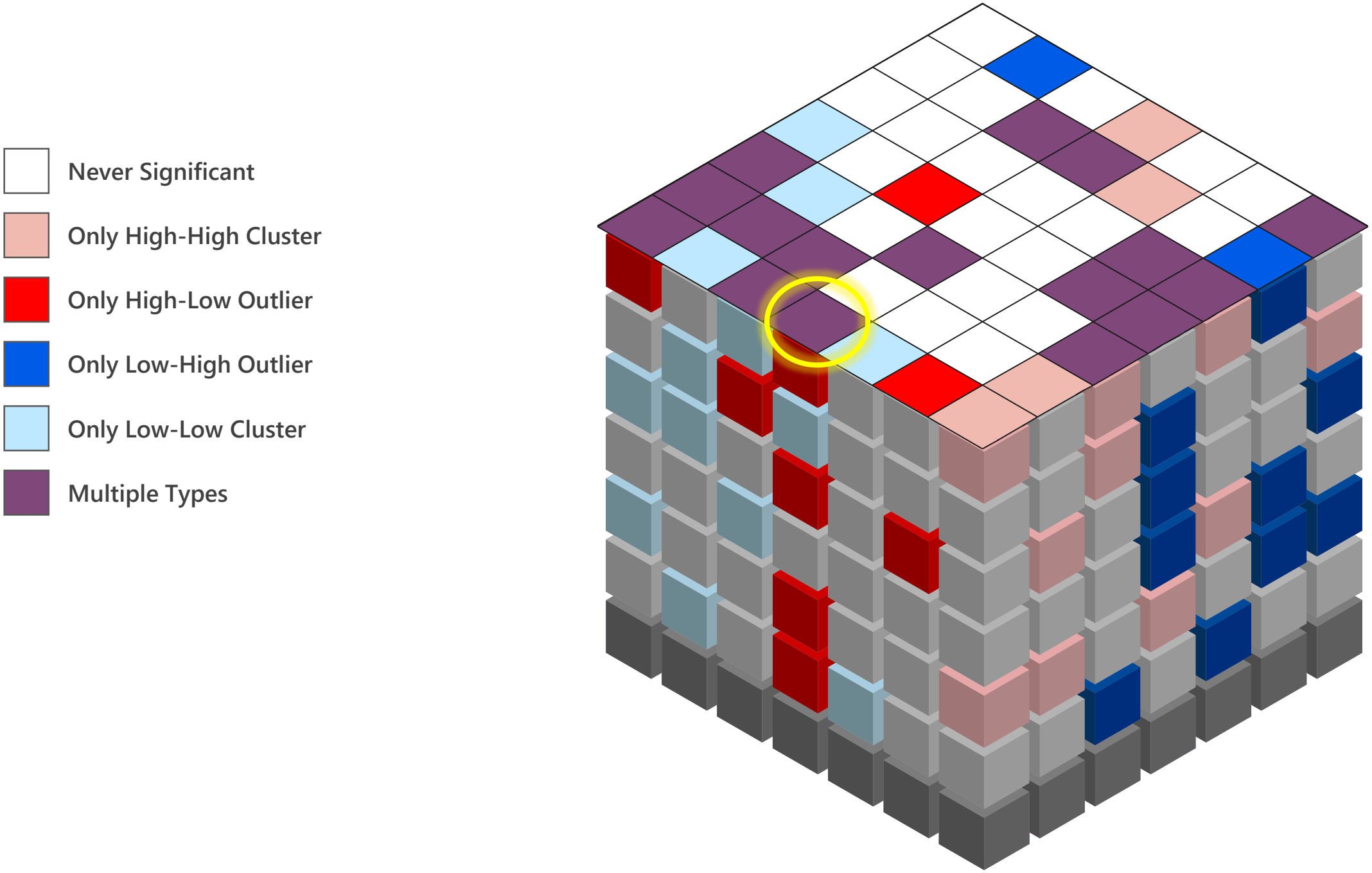
Never Significant
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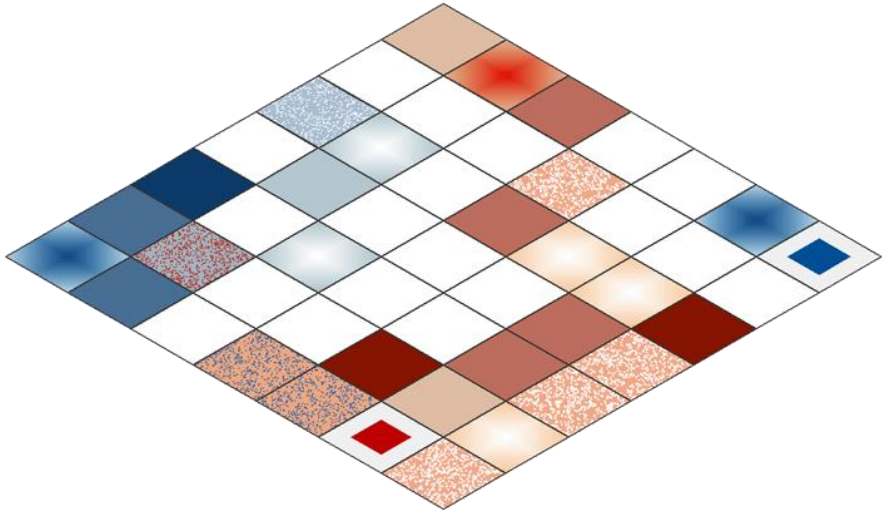
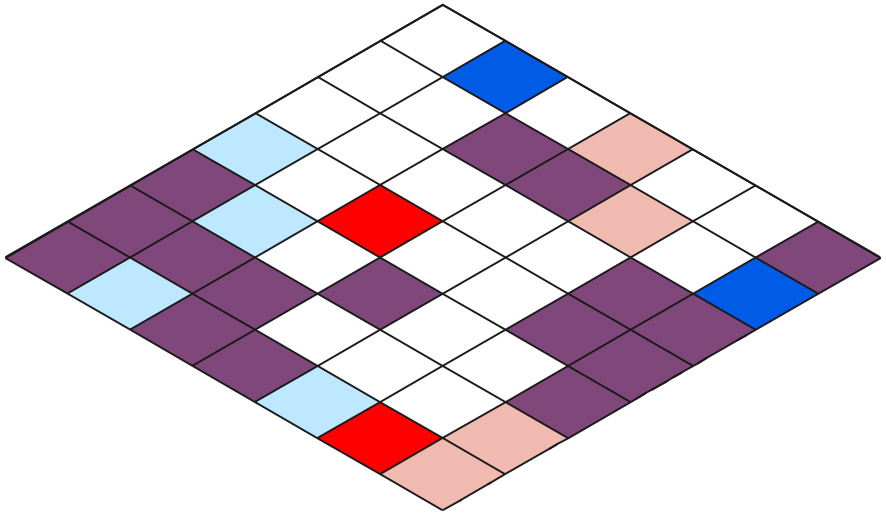
Only Low-Low Cluster
Multiple Types

demo

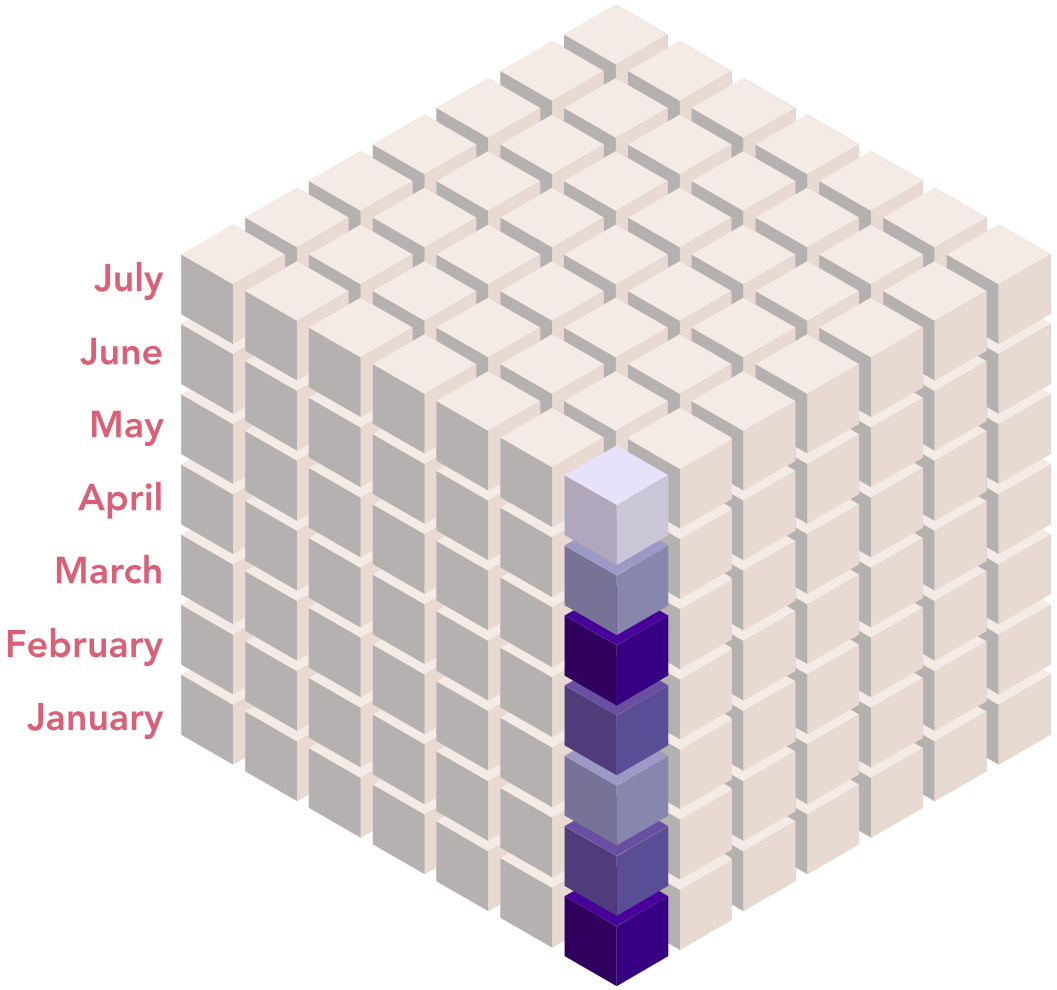




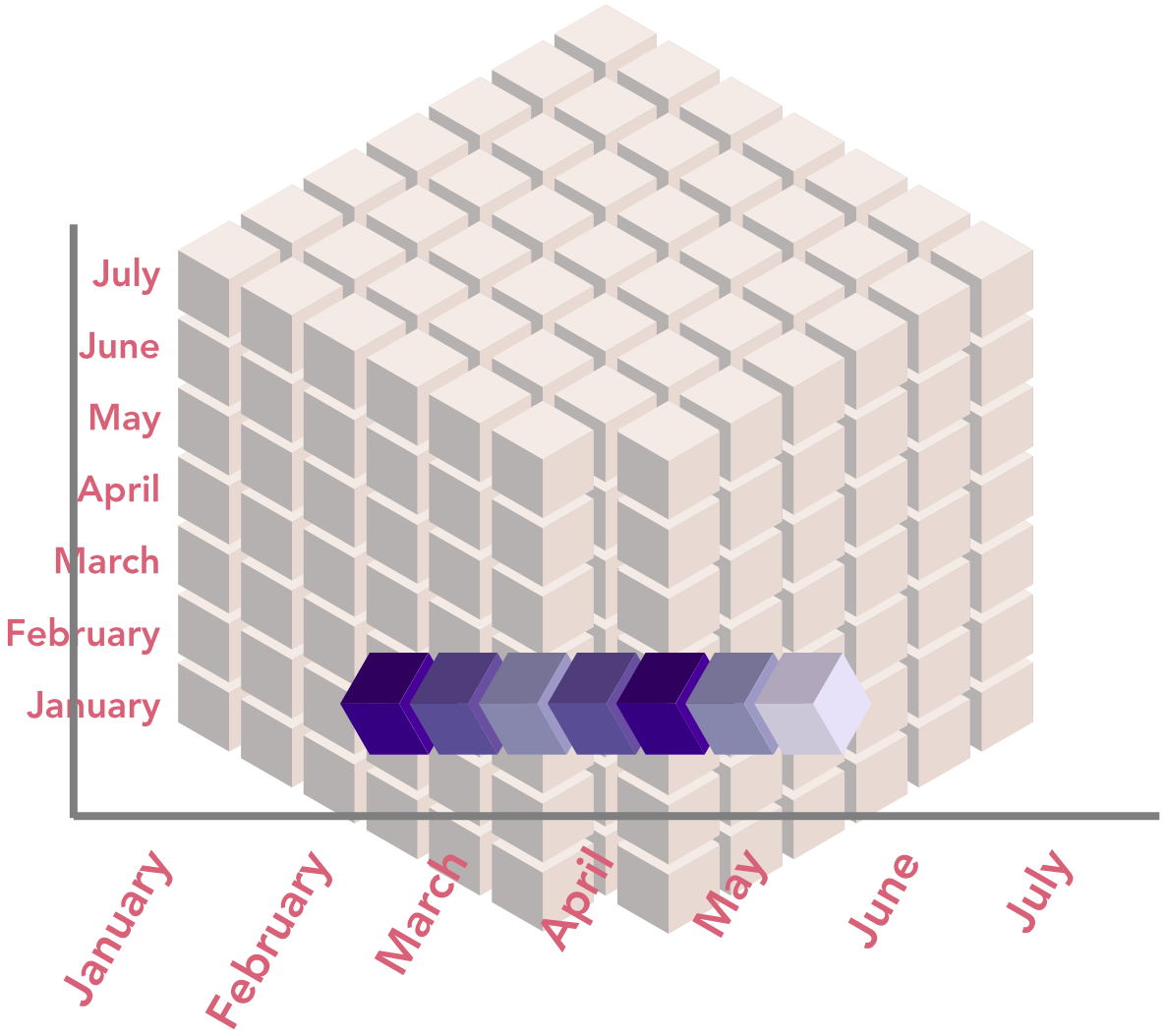
Time Series Clustering

partitions the time series in the cube based on the similarity of either value or profile

every location has a time series



every location has a time series



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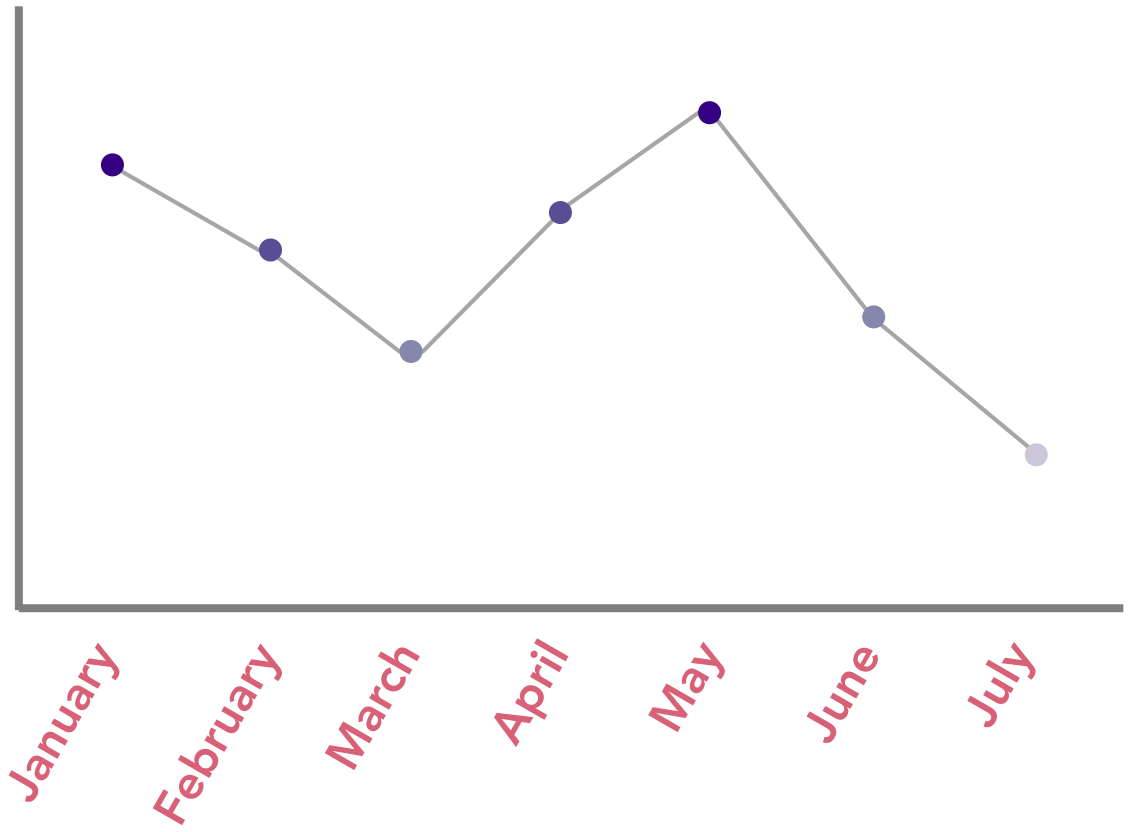
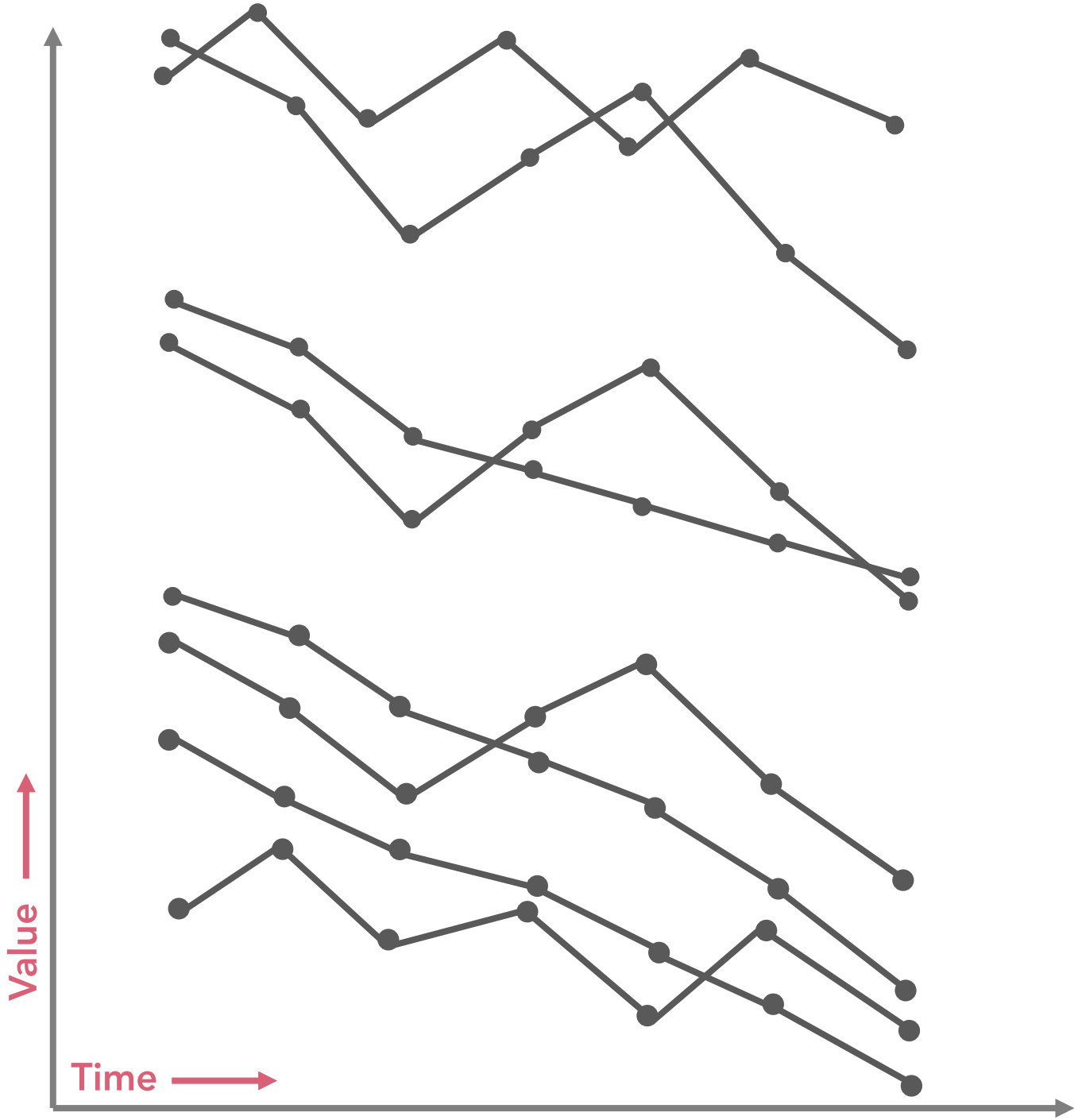
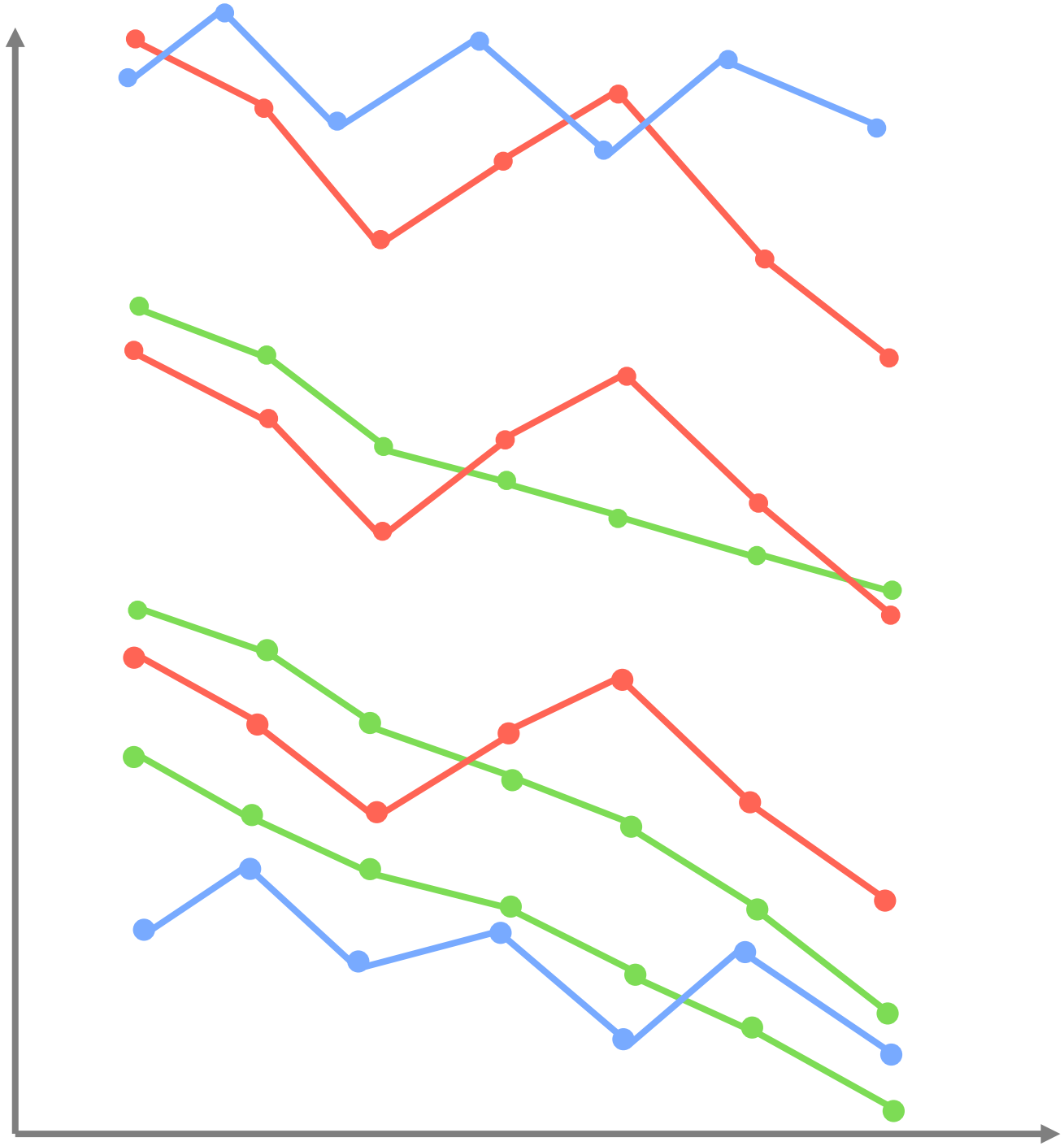


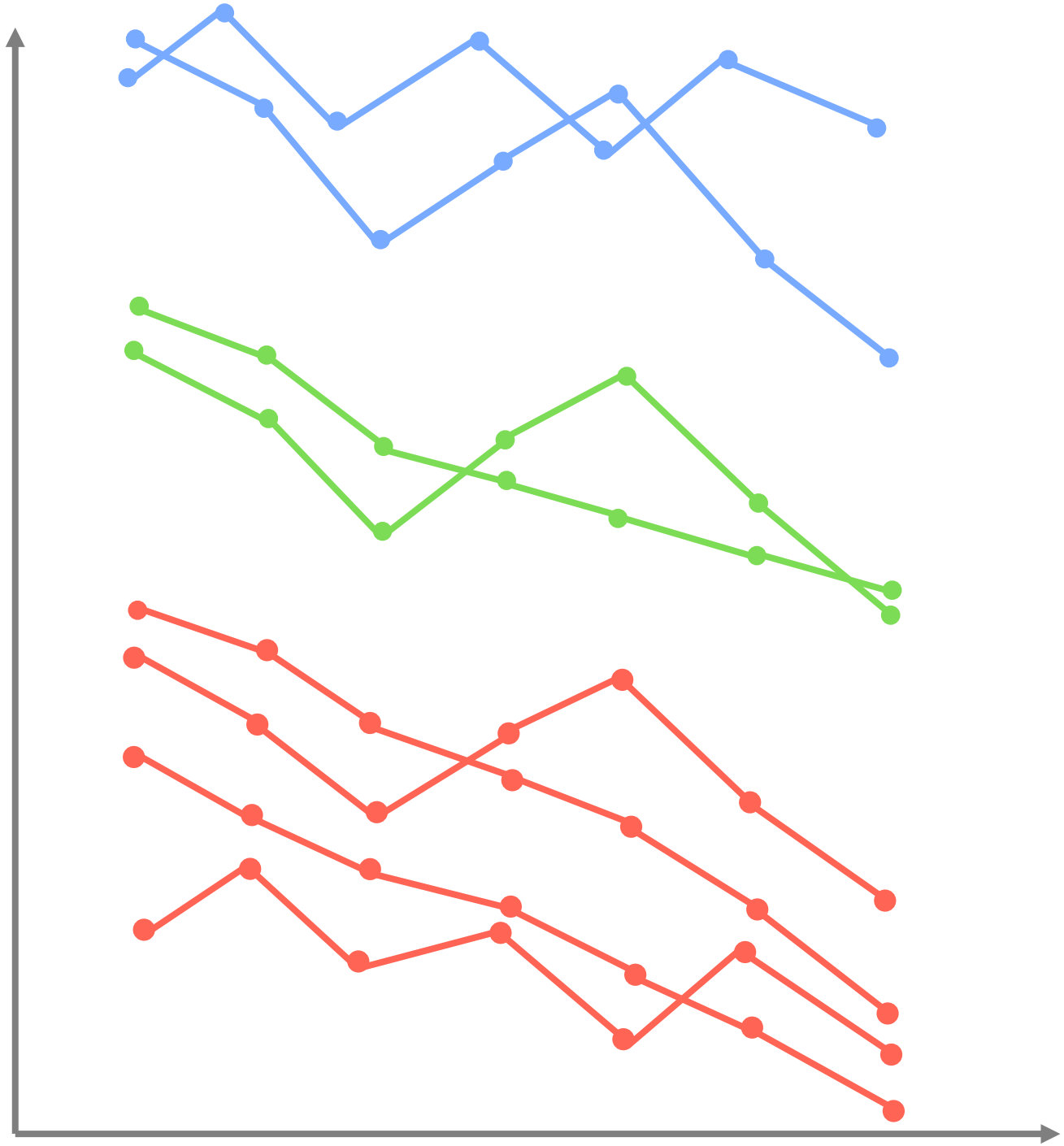
time series



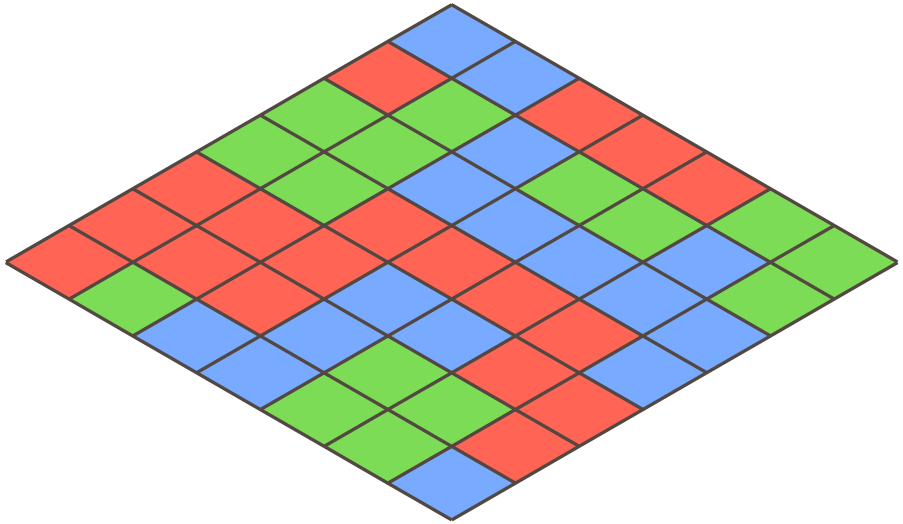
similar profiles



similar values



demo



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TUESDAY

~~8:30a From Means and Medians to Machine Learning: Spatial Statistics Basics and Innovations 15B~~

~~10a Data Visualization for Spatial Analysis 10~~

~~2:30p Spatial Data Mining I: Essentials of Cluster Analysis 15B~~

~~4p From Means and Medians to Machine Learning: Spatial Statistics Basics and Innovations 15B~~

WEDNESDAY

~~10a Spatial Data Mining II: A Deep Dive Into Space-Time Analysis Room 29C~~

~~2:30p Spatial Data Mining I: Essentials of Cluster Analysis Room 15A~~

~~4p Spatial Data Mining II: A Deep Dive Into Space-Time Analysis Room 31B~~

THURSDAY

10a Data Visualization for Spatial Analysis 07A/B

1p Beyond Where: Modeling Spatial Relationships and Making Predictions 17B

4p Beyond Where: Modeling Spatial Relationships and Making Predictions 17A

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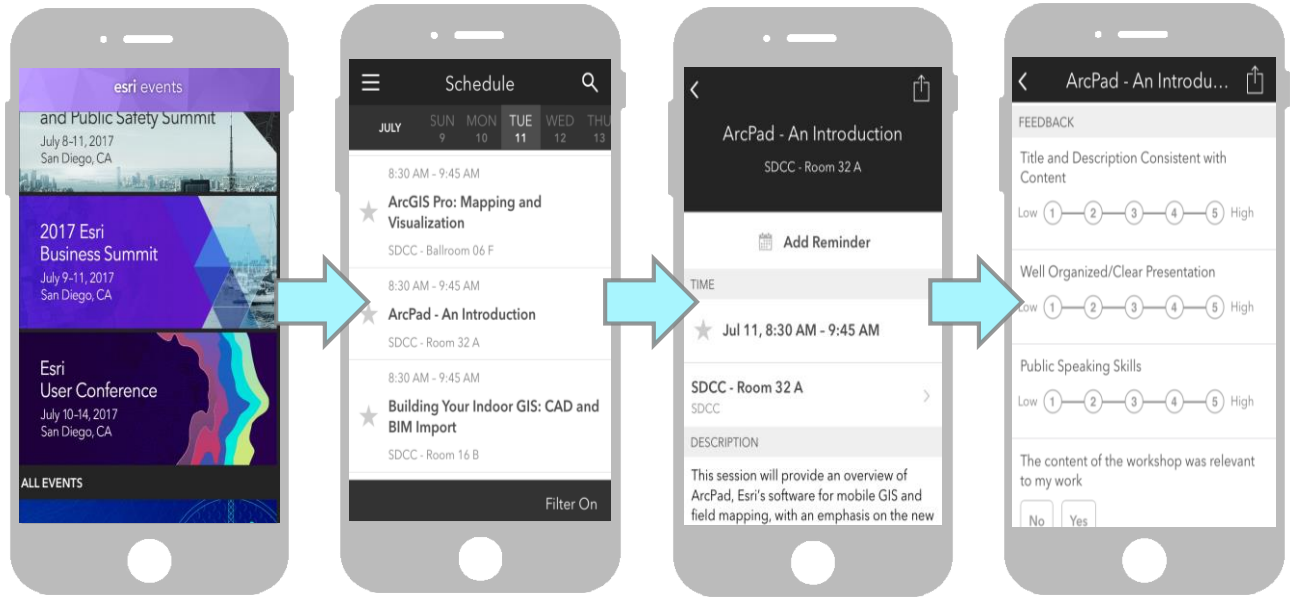

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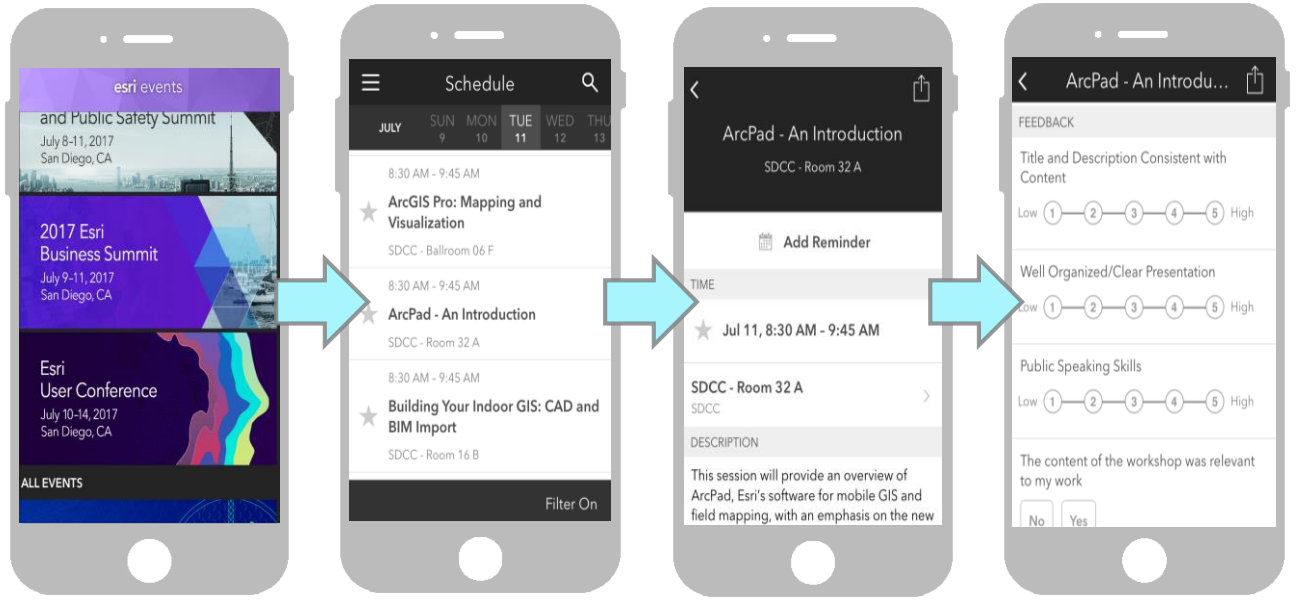
Complete Answers and Select "Submit"