TECHNOLOGICAL DRIVERS OF INNOVATIVENESS:

ASYMMETRIC RELATIONS OF PATENT ACTIVITY IN SPATIO-TEMPORAL CLUSTERS IN THE UK IN 1980-2015

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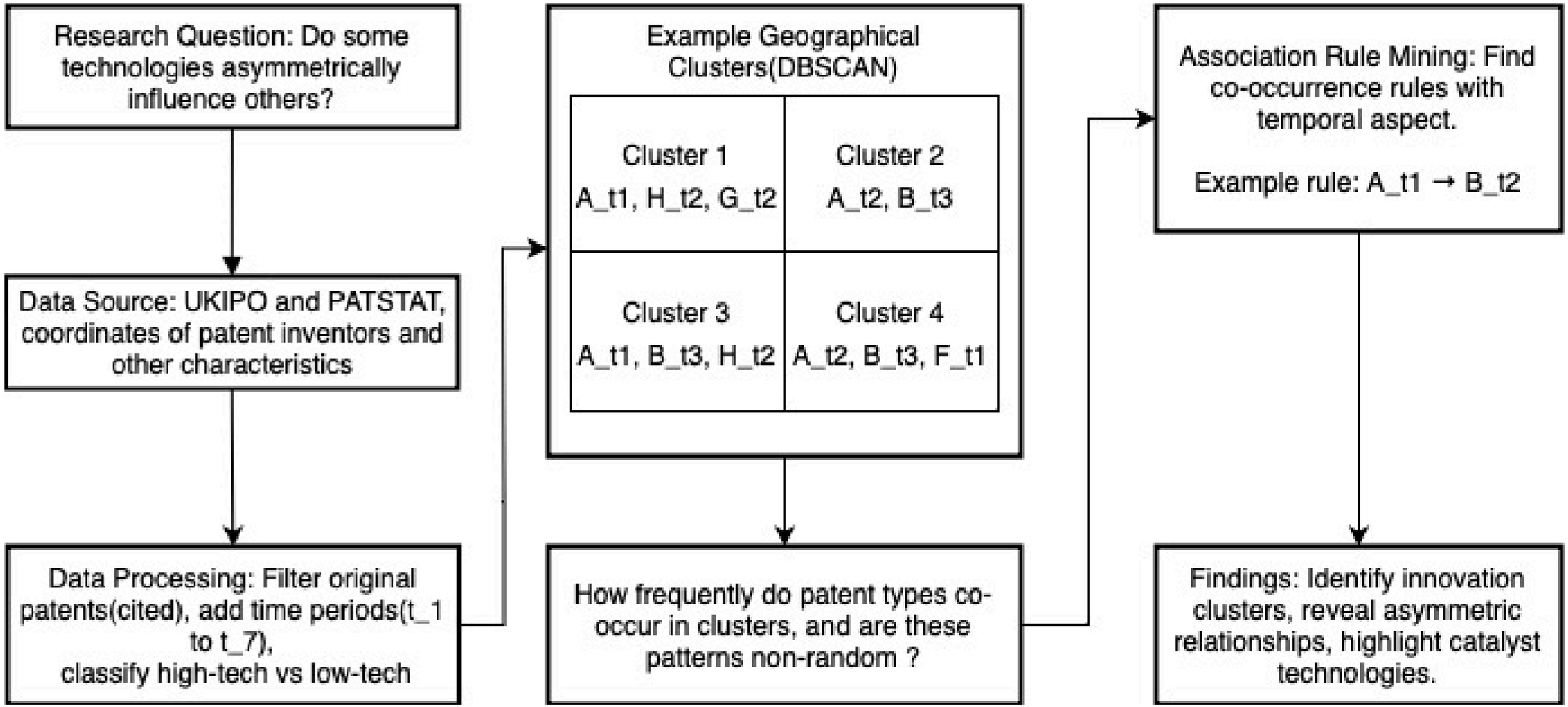
Technological relatedness refers to the degree of similarity between different technologies, in terms of their co-occurrence in regions, which can facilitate innovation or capabilities across related industries or fields.

(Boschma et al., 2022)

Why Asymmetric Relatedness matters?

Asymmetric relatedness shows how some technologies spark the growth of others, driving innovation and regional development.

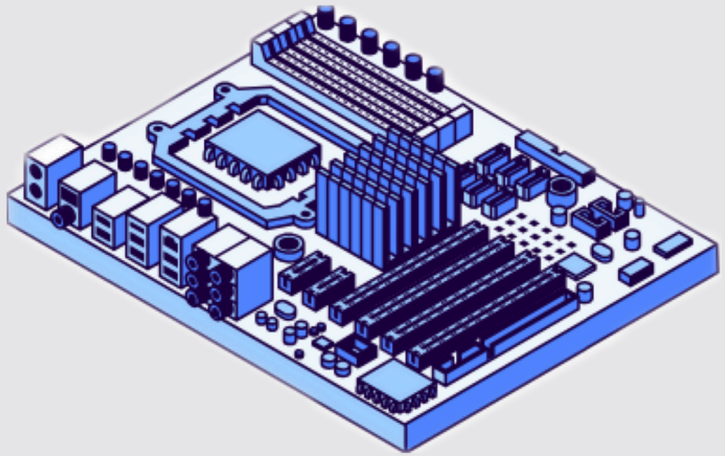
Diagram showing the analytical workflow combining spatial clustering and association rule mining



Why new methods are needed ?

Current relatedness methods can’t provide asymmetric rules

(Boschma, 2017)



Software

Hardware

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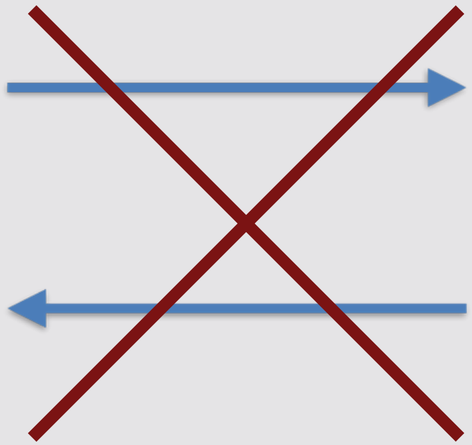
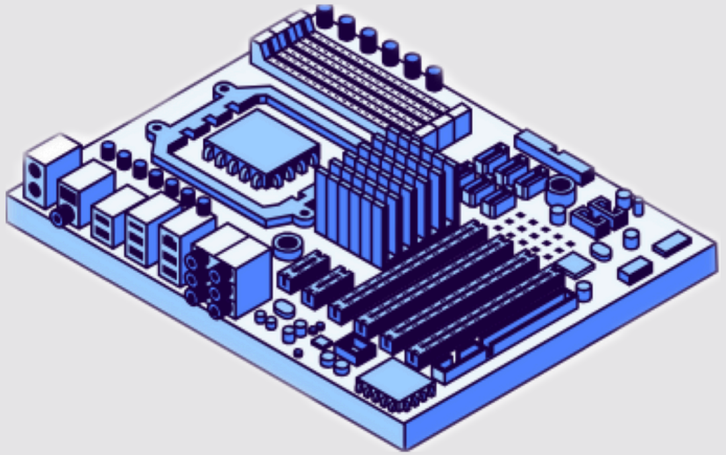
(Boschma, 2017)





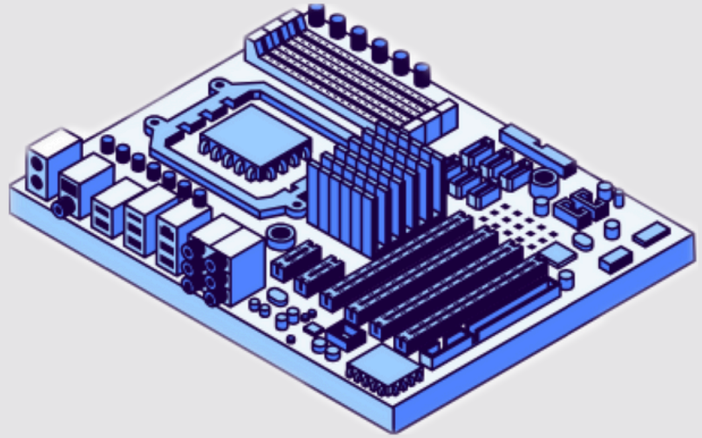
Software

Hardware

Why new methods are needed ?

In reality relatedness is asymmetric most of the time

(Boschma, 2017)



Software

Hardware

Data: Cited Patents

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21292583	52.57612	-1.9490919	F24F	2000-01-05
21292591	52.62726	-0.5079481	A47K	2000-01-05
21292609	51.39139	-0.0255888	B65G	2000-03-14
21292611	52.60643	-1.1182190	H04M	2000-01-05
21292623	51.55675	0.7009875	A61B	2000-01-05
21292681	51.31396	-0.1537878	E02D	2000-01-05
21292814	51.50845	-1.5255141	G01K	2000-01-07
21292820	53.78000	-0.4175816	A61L	2000-01-07
21292956	51.29177	-1.0578076	A47J	1998-07-13
21292979	51.55773	-0.3771354	B23B	2000-01-06

1–10 of 26,976 rows

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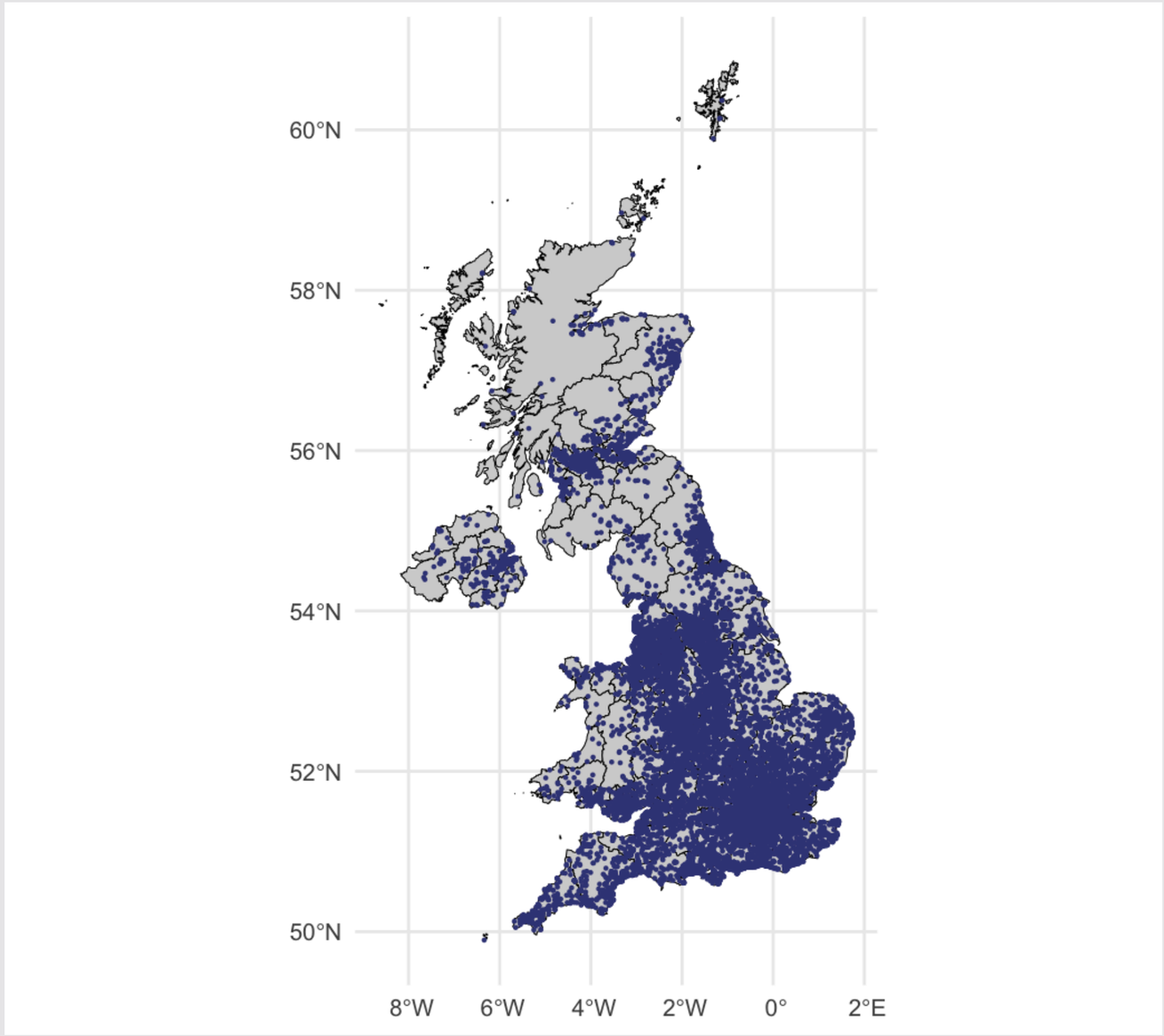
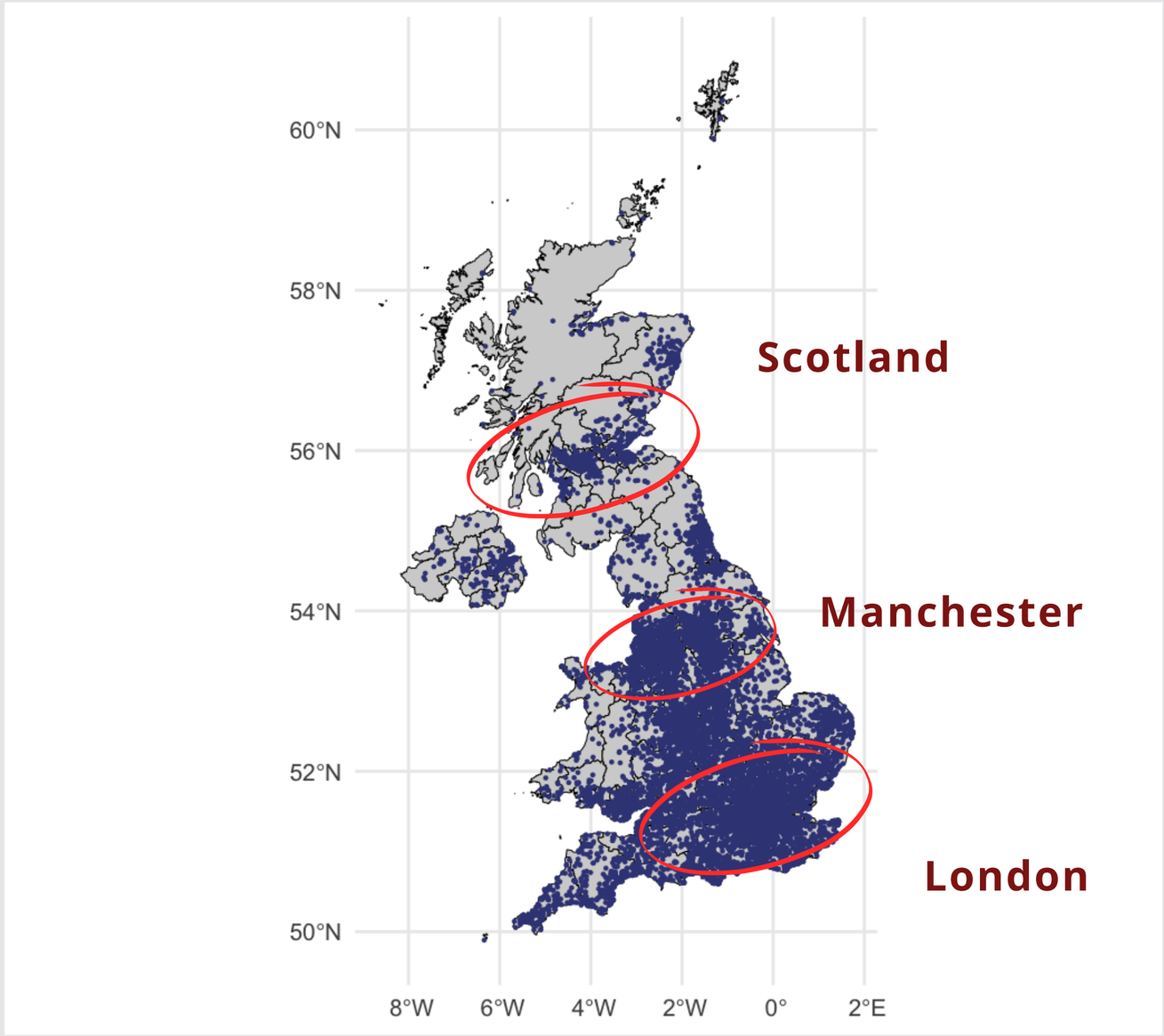
Locations of Patents



Locations of Patents

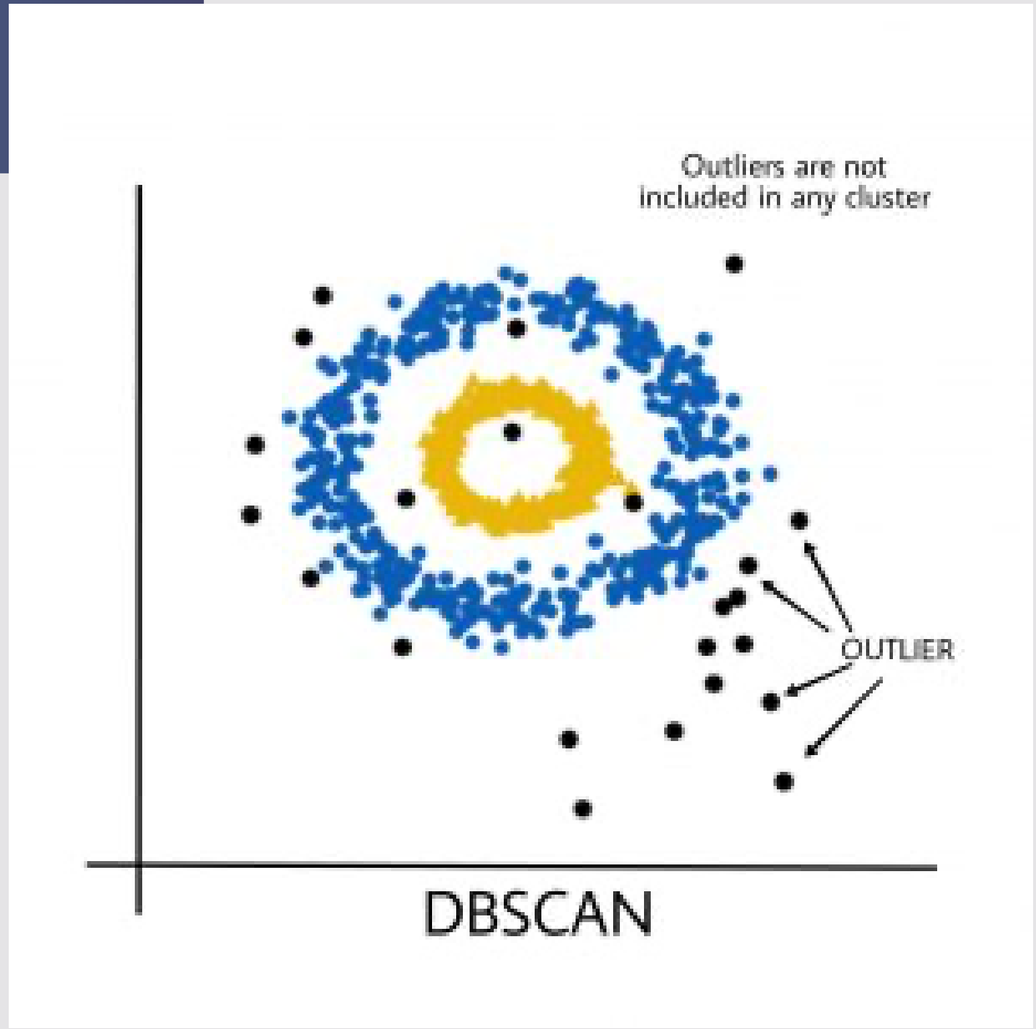


DBSCAN Algorithm

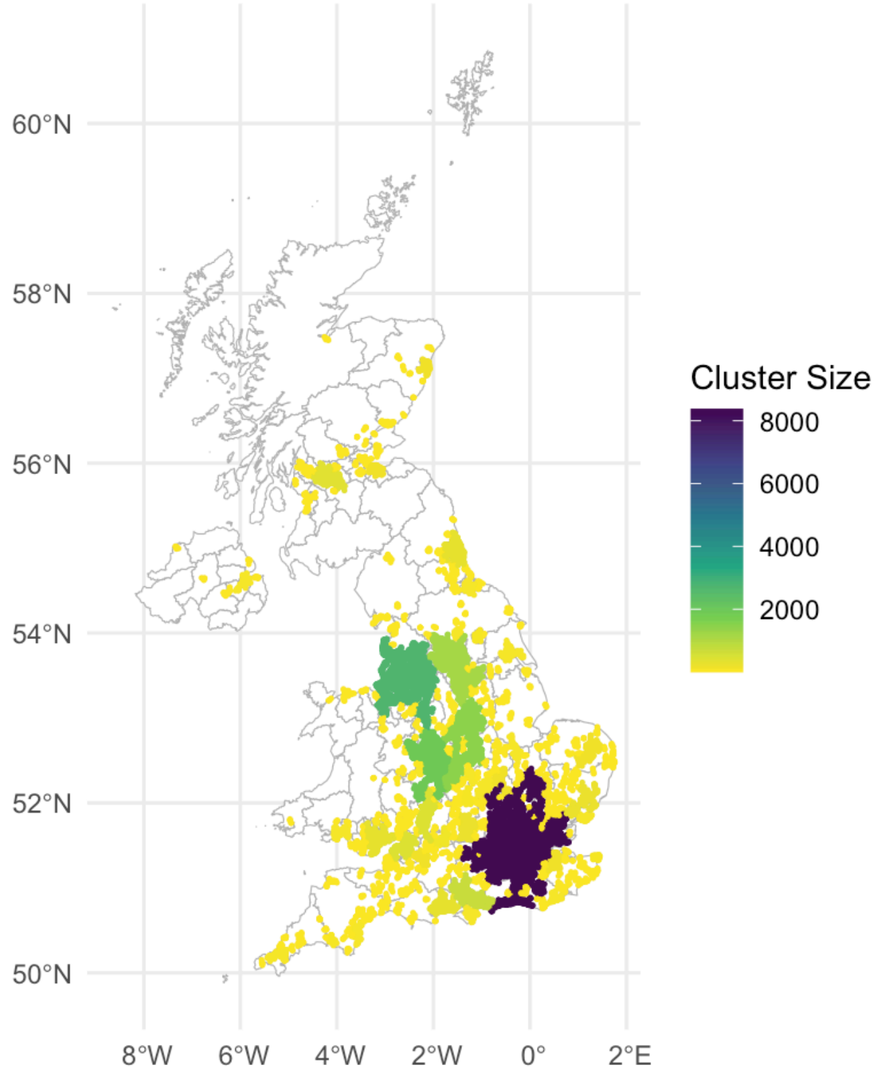
DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a clustering algorithm that groups together points that are closely packed while marking points in low-density regions as outliers. It’s particularly useful for discovering clusters of arbitrary shapes.

Two parameters:

minPts and epsilon(distance)



DBSCAN Clustering

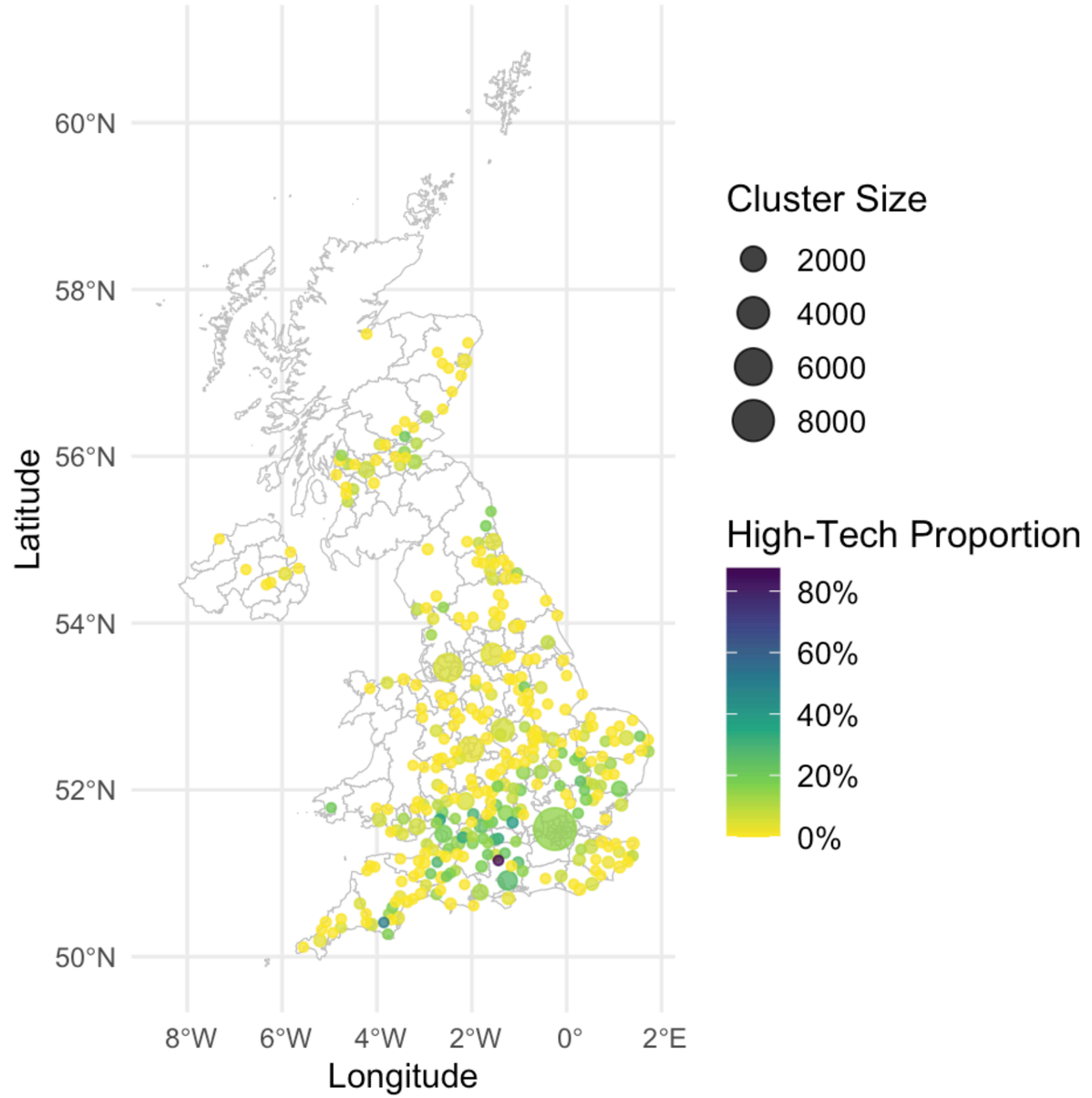


Parameters: eps = 0.045, minPts = 5

The clustering contains 341 cluster(s) and 1799 noise points.

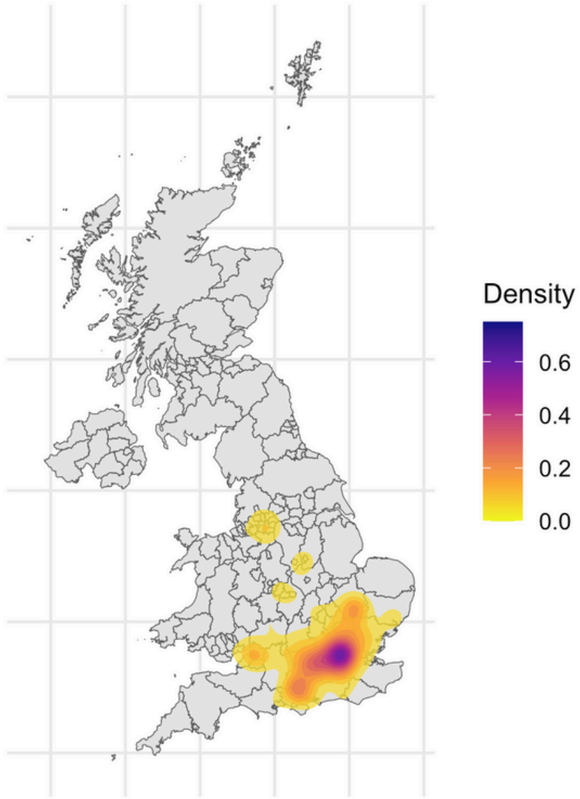
Darker color represents bigger cluster size

Proportion of High-Tech

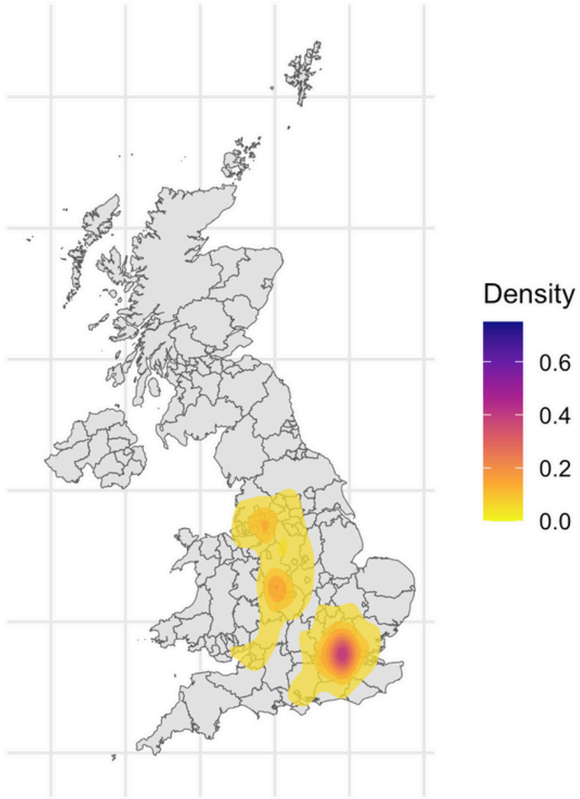


Kernel Density Estimation

High-tech



Low-tech



Association Rule Mining: Market Basket Analysis

- A data mining technique used to find relationships between items in large datasets.
- Commonly used to identify products frequently bought together in market transactions.

Final Data for Association Rule Mining

	LHS	RHS	support	confidence	coverage	lift	count
	All	All	All	All	All	All	All
[1693]	{E06B_t4_Low-Tech,H04Q_t3_High-Tech}	{H04R_t3_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3556]	{B60R_t4_Low-Tech,B65D_t3_Low-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3565]	{B60R_t4_Low-Tech,H04Q_t5_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3568]	{B60R_t4_Low-Tech,H04N_t5_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3571]	{B60R_t4_Low-Tech,G06F_t3_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3574]	{B60R_t4_Low-Tech,H04M_t4_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3577]	{B60R_t4_Low-Tech,H04B_t4_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3595]	{H04N_t4_High-Tech,H04Q_t5_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3607]	{H04B_t4_High-Tech,H04N_t4_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000
[3619]	{B65D_t3_Low-Tech,G06F_t2_High-Tech}	{H01L_t6_High-Tech}	0.020	1.000	0.020	49.600	5.000

Showing 1 to 10 of 3,017 entries

Final Data for Association Rule Mining

	LHS	RHS	support	confidence	coverage	lift	count
	All	All	All	All	All	All	All
[1693]	{E06B_t4_Low-Tech,H04Q_t3_High-Tech}	{H04R_t3_High-Tech}	0.020	1.000	0.020	49.600	5.000
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Showing 1 to 10 of 3,017 entries

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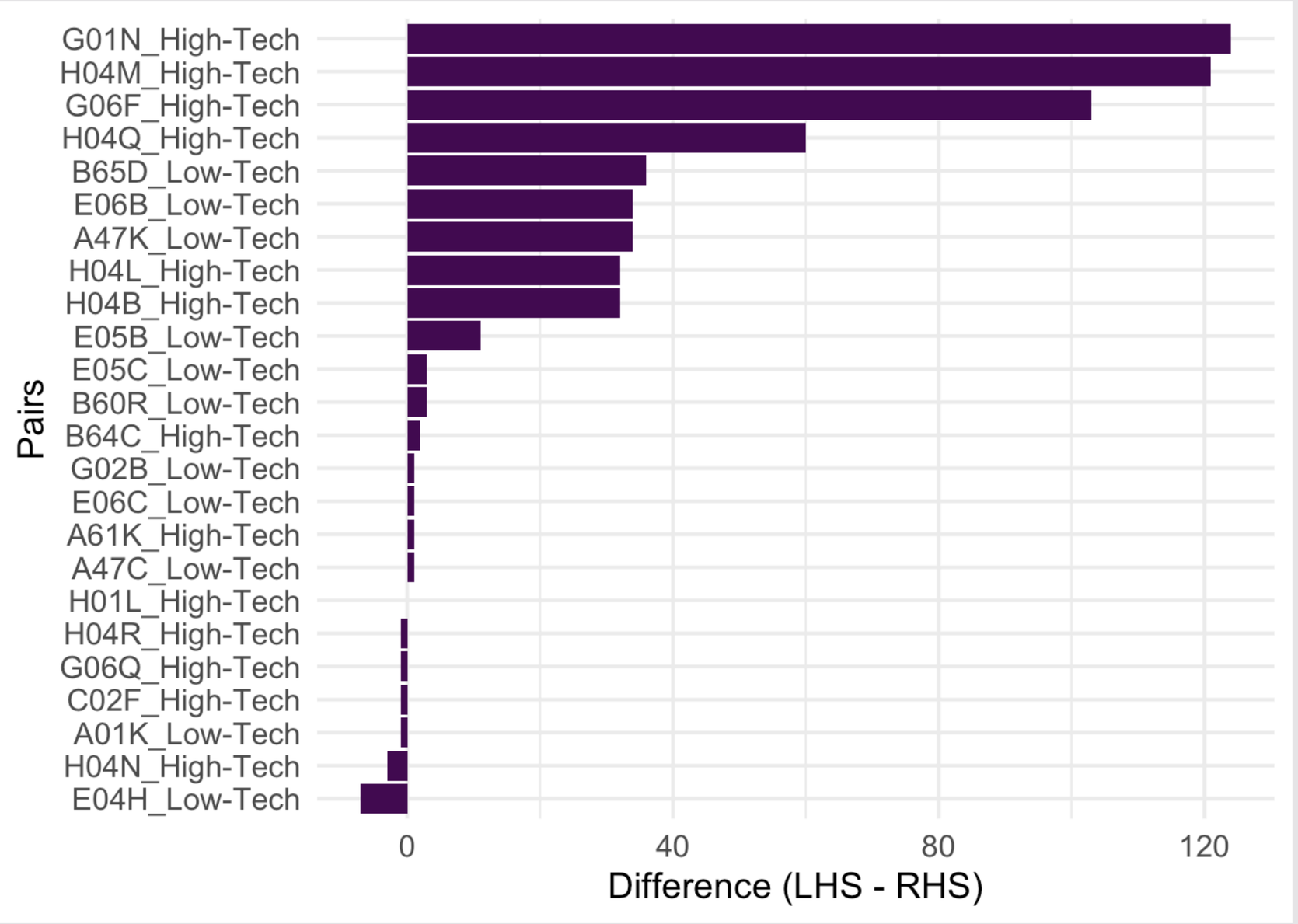
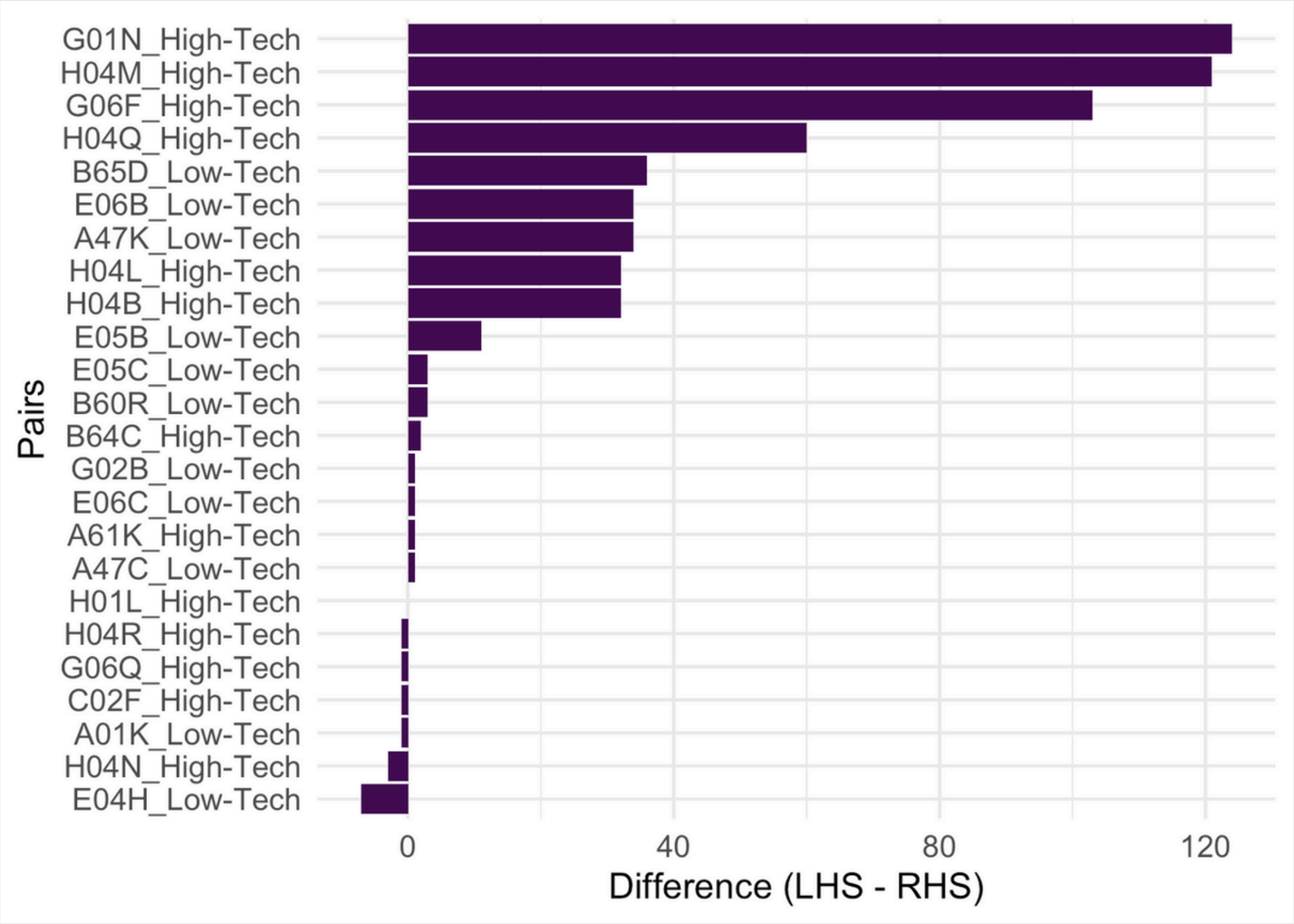
Most common driver technologies



Most common driver technologies

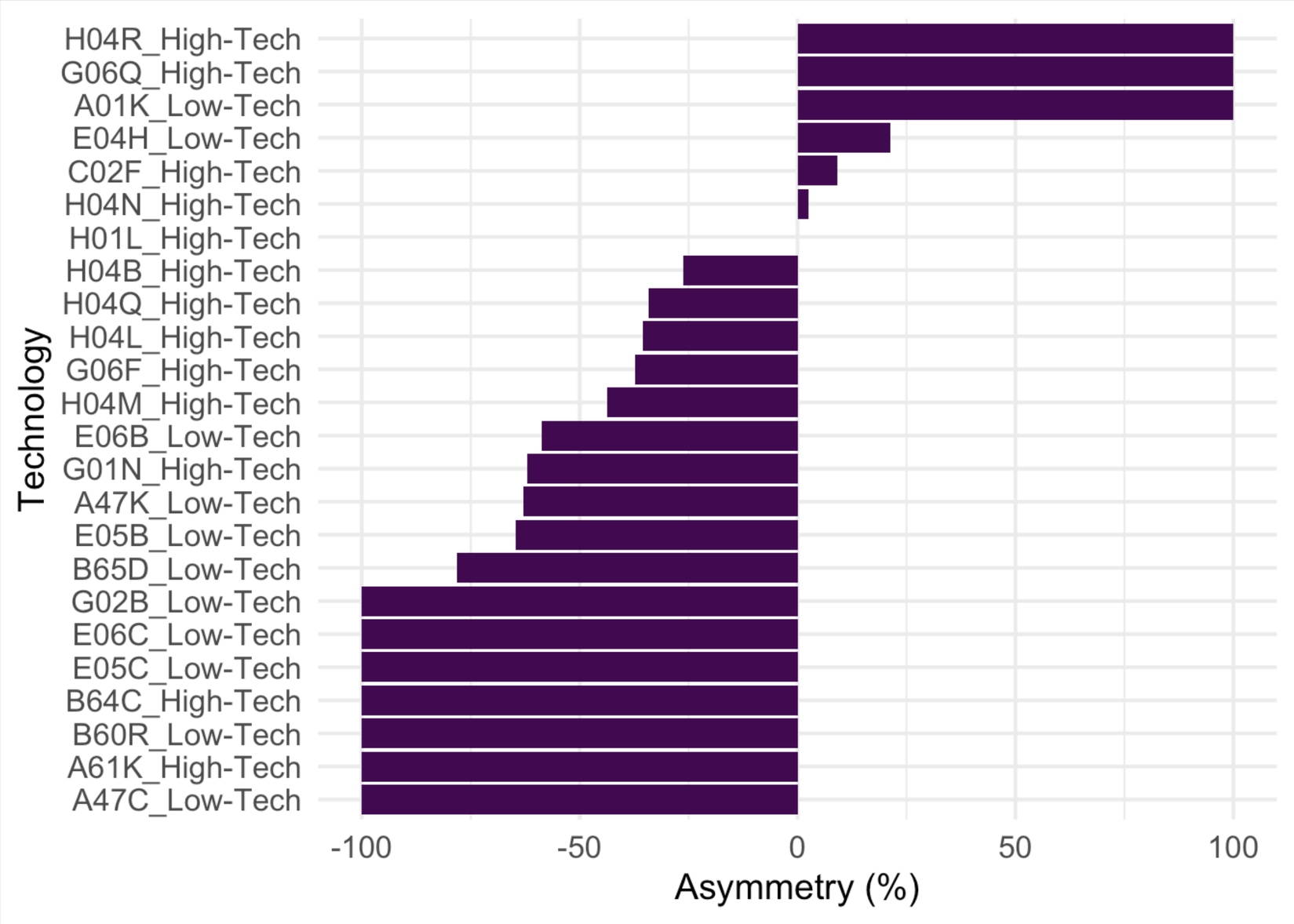


This plot highlights the top driver patents, those that occur significantly more often as the Left-Hand Side (LHS, "IF") in association rules compared to the Right-Hand Side (RHS, "THEN").

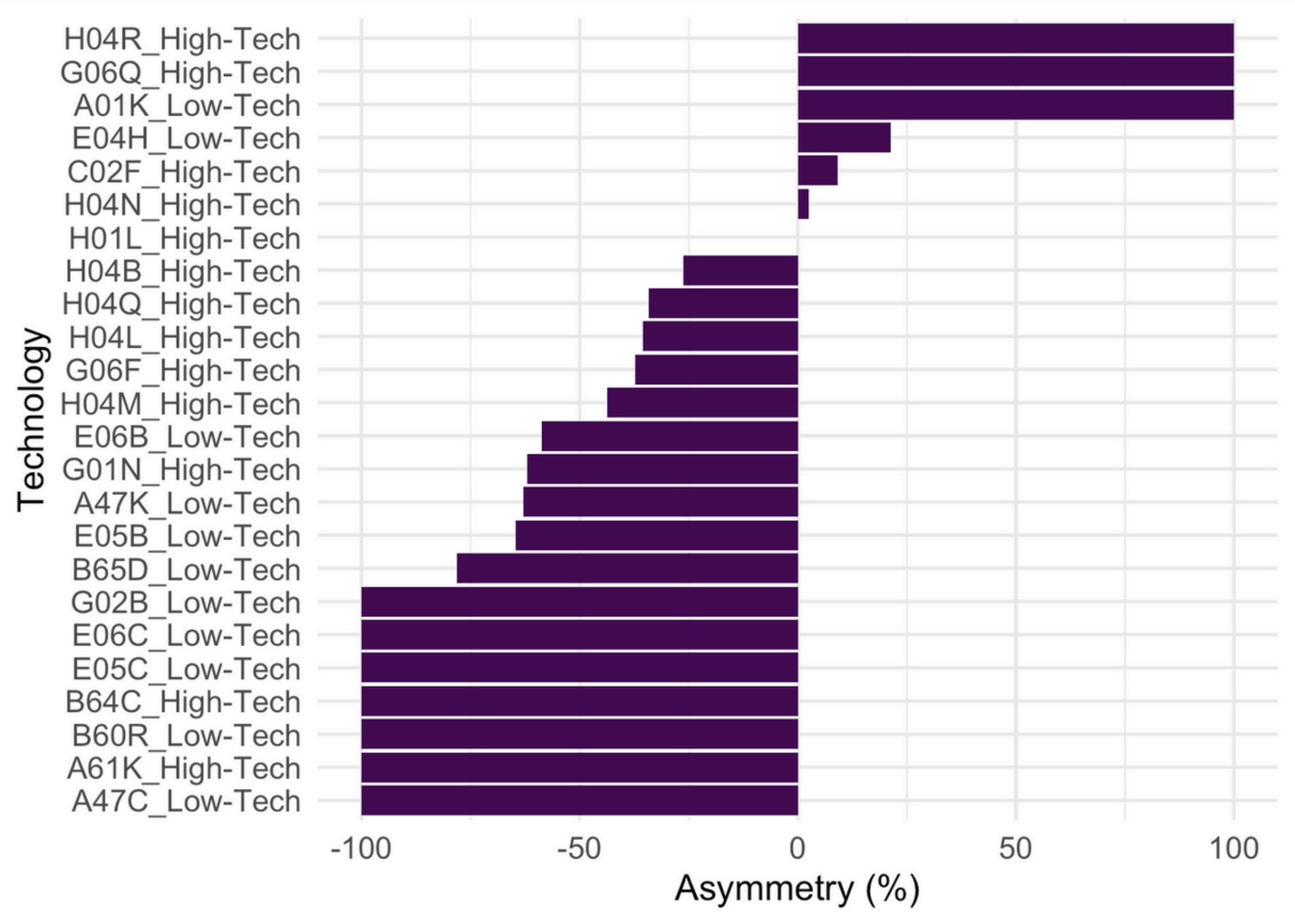
These patents serve as key initiators or enablers in the context of technological relatedness, indicating that their presence is likely to drive or influence the occurrence of other technologies.

G06F (Electric digital data processing) is one of the most common driver technology.

Most common driver technologies by proportions



Most common driver technologies by proportions



Interestingly, both high-tech (e.g. G01N and H04M) and low-tech (e.g. B65D and E06B) technologies appear as influential LHS components. This suggests that influence depends not only on technological classification, but also on the specific role that a technology plays within the innovation system.

This asymmetry in positioning within association rules provides meaningful insight into the directionality of innovation flows and helps identify potential catalyst technologies.

High-Tech Low-Tech Occurance Matrix

IF \ THEN	High-Tech	Low-Tech
High-Tech	68.0%	8.2%
Low-Tech	18.2%	5.6%

High-Tech Low-Tech Occurance Matrix

IF \ THEN	High-Tech	Low-Tech
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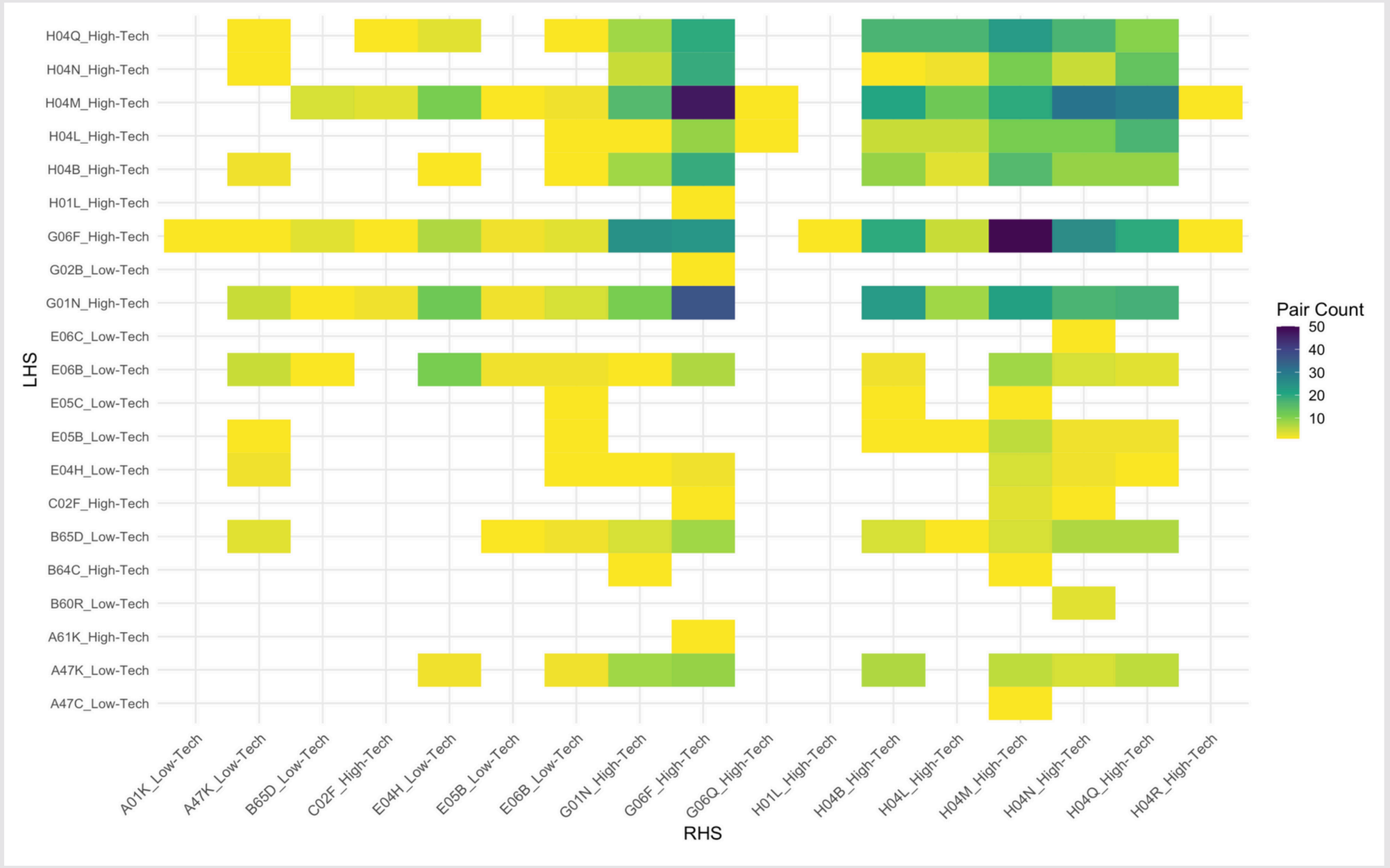
This matrix reveals a clear asymmetry in technological influence between high-tech and low-tech patents. When a high-tech patent appears first, another high-tech patent follows in 68% of cases (2/3 of rules), whereas a low-tech follow-up occurs in only 8.2% of cases (1/12). Conversely, low-tech patents are followed by high-tech patents in 18.2% of cases and by other low-tech patents in just 5.6% of cases.

High-Tech Low-Tech Occurance Matrix

IF \ THEN	High-Tech	Low-Tech
High-Tech	68.0%	8.2%
Low-Tech	18.2%	5.6%

These findings suggest that high-tech patents are self-reinforcing and play a central role in shaping the innovation landscape. Their influence extends beyond their own domain, reinforcing their position as catalyst technologies. In contrast, low-tech patents tend to play a more passive role, rarely driving subsequent innovation within or outside their category.

Most Assymetric Pair of Technologies



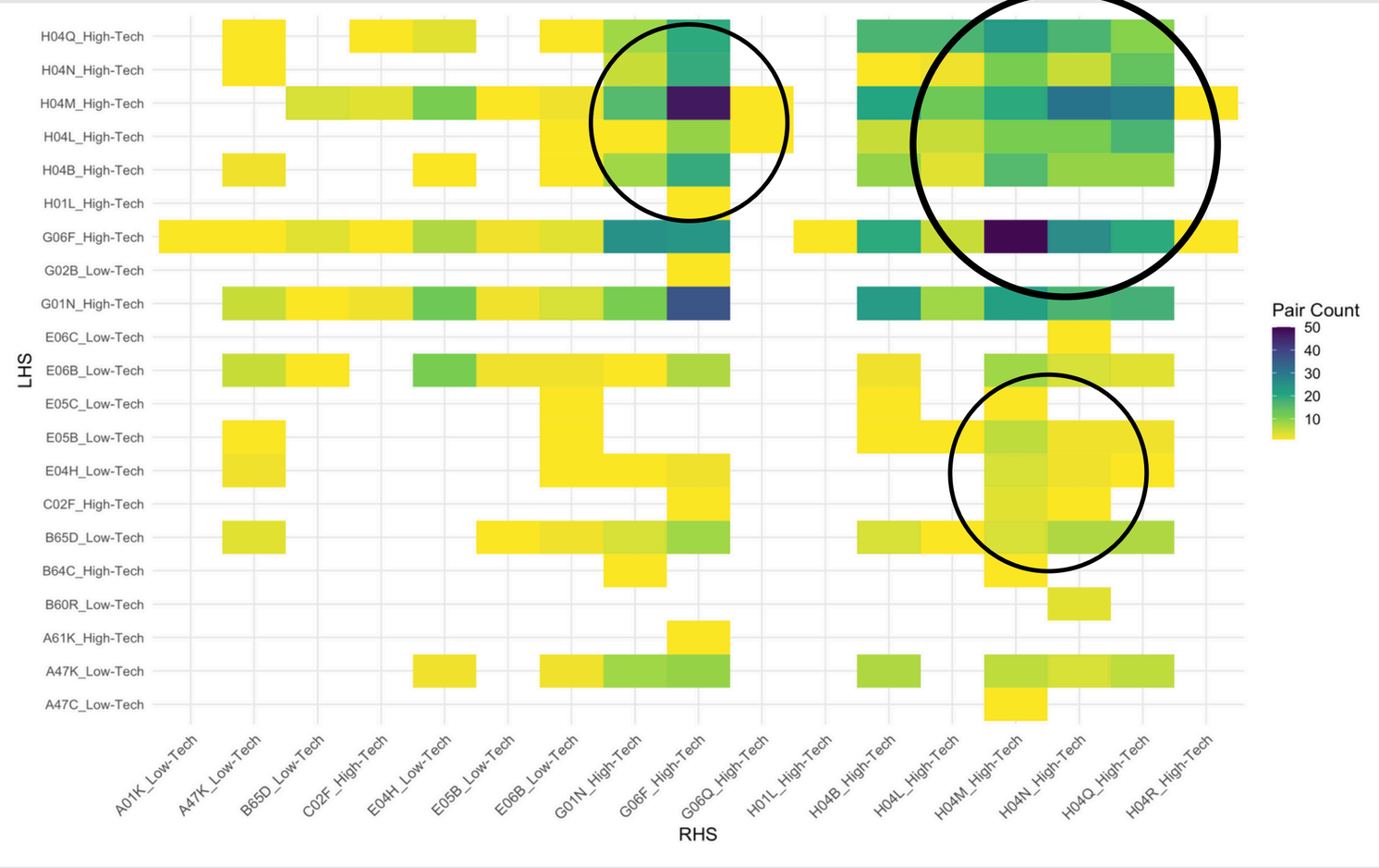
Most Assymetric Pair of Technologies

G01N and E04H one of the most assymetric pair of technology

Technology Clusters based on Heatmap

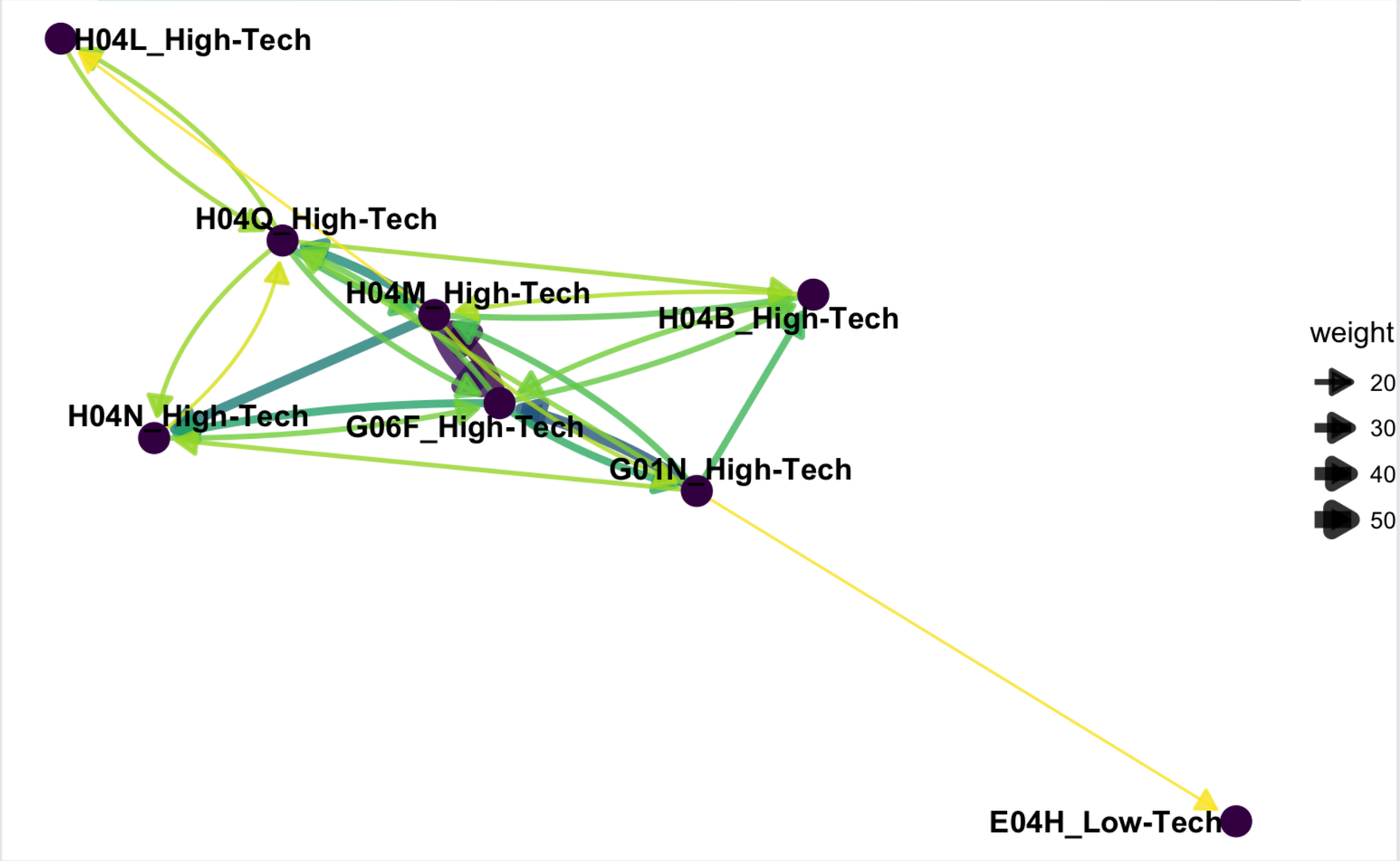
The heatmap
reveals notable clustering patterns, showing that specific technologies frequently co-occur in
rules and form strong associations. For example: H04Q (selecting), H04N (pictorial
communication, e.g. television), H04M (telephonic communication) and H04L (transmission
of digital information, e.g. telegraphic communication) frequently appear together in rules,
indicating dense interaction networks among these technologies.
coherent domain enhances innovation and knowledge spillover opportunities.

Technology Clusters based on Heatmap



These clusters suggest technological areas in which joint innovation is common. The presence of these dense interaction zones lends weight to the idea that certain technological fields evolve as interconnected clusters rather than in isolation. These technological clusters may reflect shared knowledge bases or functional interdependencies.

Network Graph of Related Patents



H04Q (Selecting), H04N (Pictorial communication e.g. Television), H04M (Telephonic communication) and H04L (Transmission of digital information, e.g. Telegraphic communication)

Conclusion

- Technologies are asymmetrically related, playing the causal roles of antecedents and consequents
- High-tech patents influence low-tech more than the opposite
- The dynamic association rules revealed asymmetric causal influences across technologies, highlighting key catalyst technologies
- Patents in telecommunications frequently affect each other and are important drivers of technological clusters

I would like to hear your comments and questions.

Thank you !

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