Advanced Data Management (CSCI 490/680)

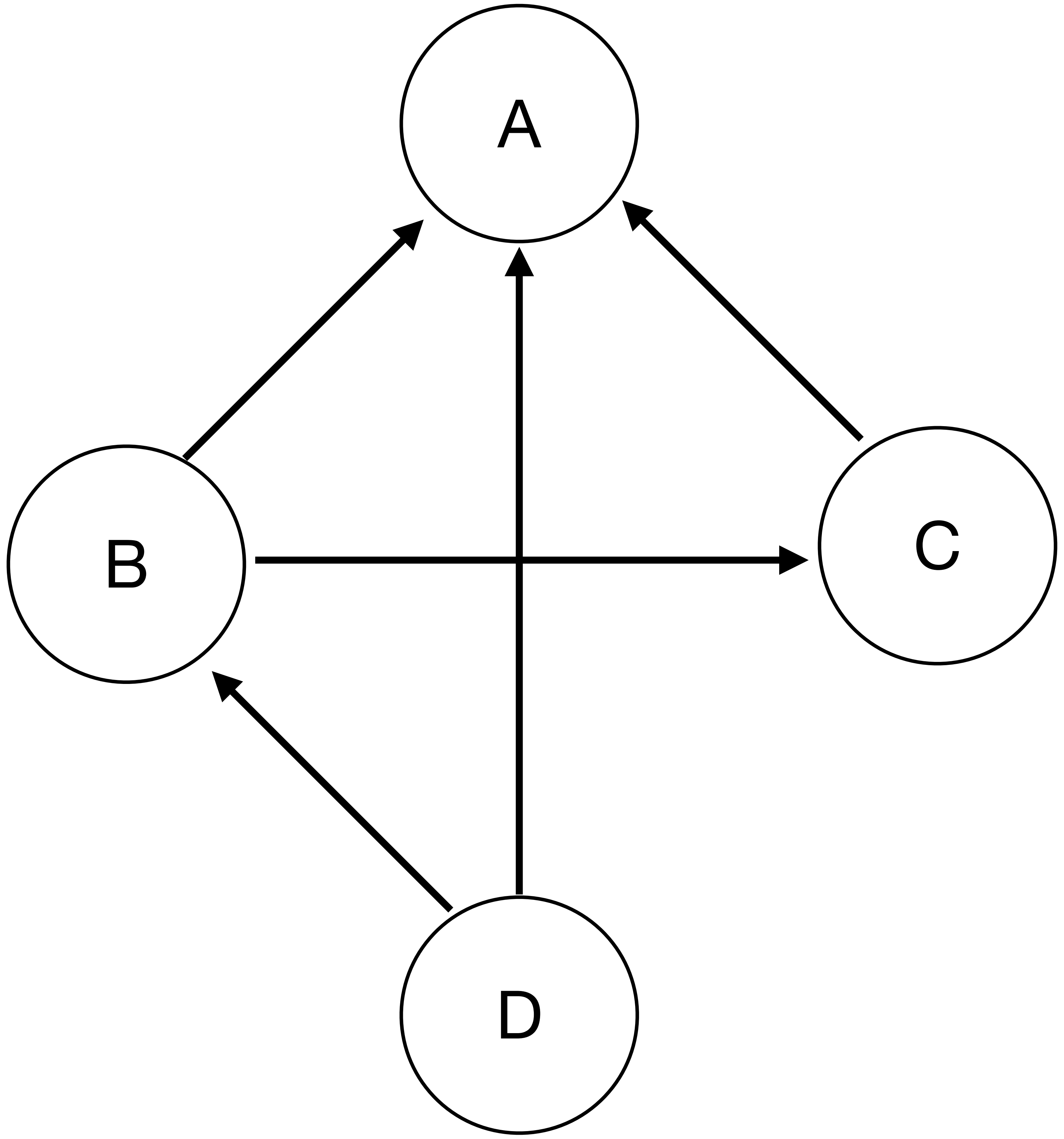
Visualization and Databases

Dr. David Koop

pandas 2.0 Released Last Monday

- dtype_backend can be pyarrow
- Number of changes to datetime
  - UTC, datetime[s], parsing
  - https://pandas.pydata.org/pandas-docs/version/2.0.0/whatsnew/v2.0.0.html#datetimes-are-now-parsed-with-a-consistent-format

Graphs

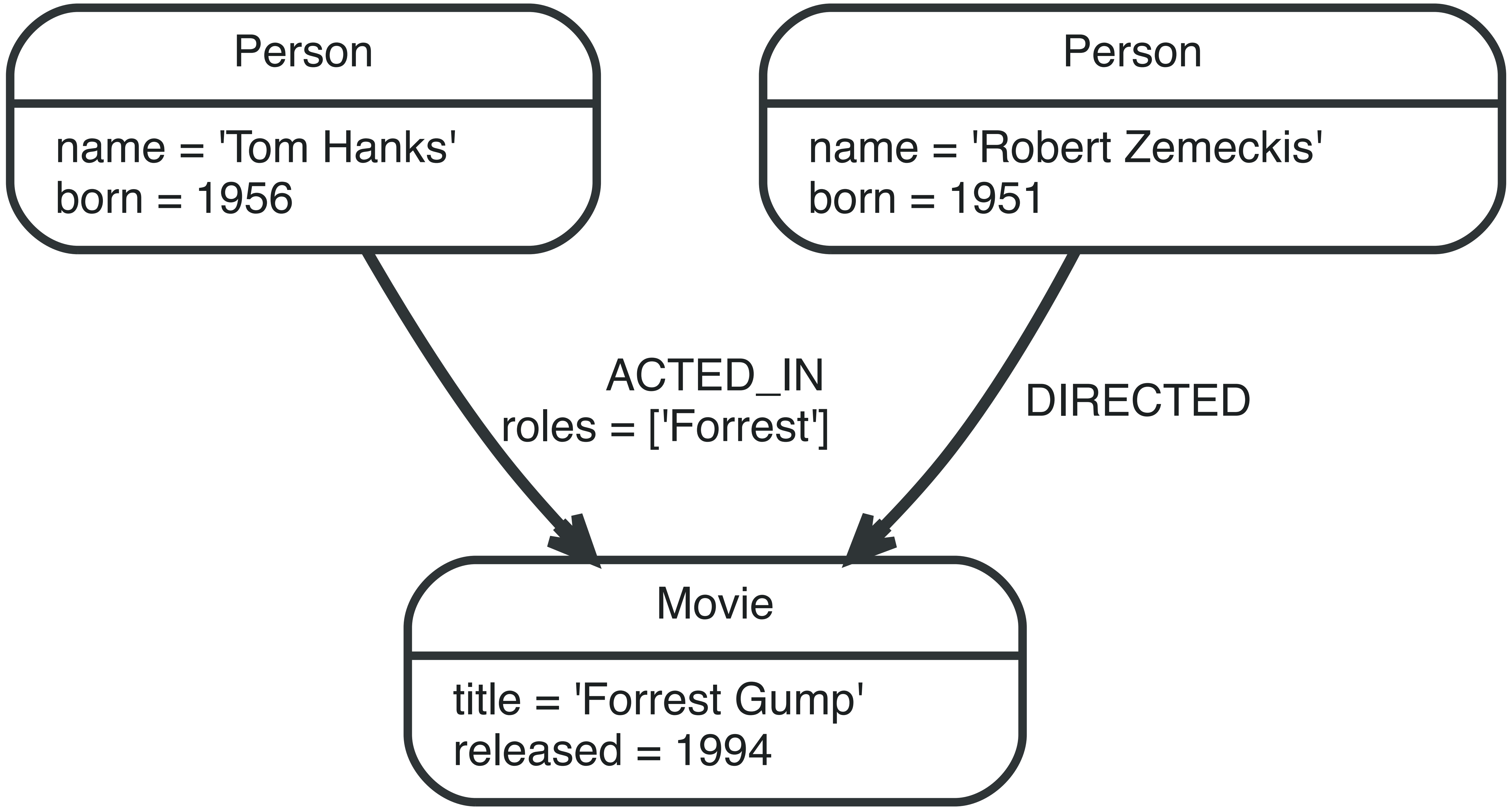


- In computing, a **graph** is an abstract **data structure** that represents set objects and their relationships as **vertices** and **edges/links**, and supports a number of graph-related **operations**
- Objects (nodes): `{A,B,C,D}`
- Relationships (edges): `{(D,B),(D,A),(B,C),(B,A),(C,A)}`
- Operation: shortest path from `D` to `A`

[K. Salama, 2016]

Graphs with Properties

- Each vertex or edge may have properties associated with it
- May include identifiers or classes



[neo4j]

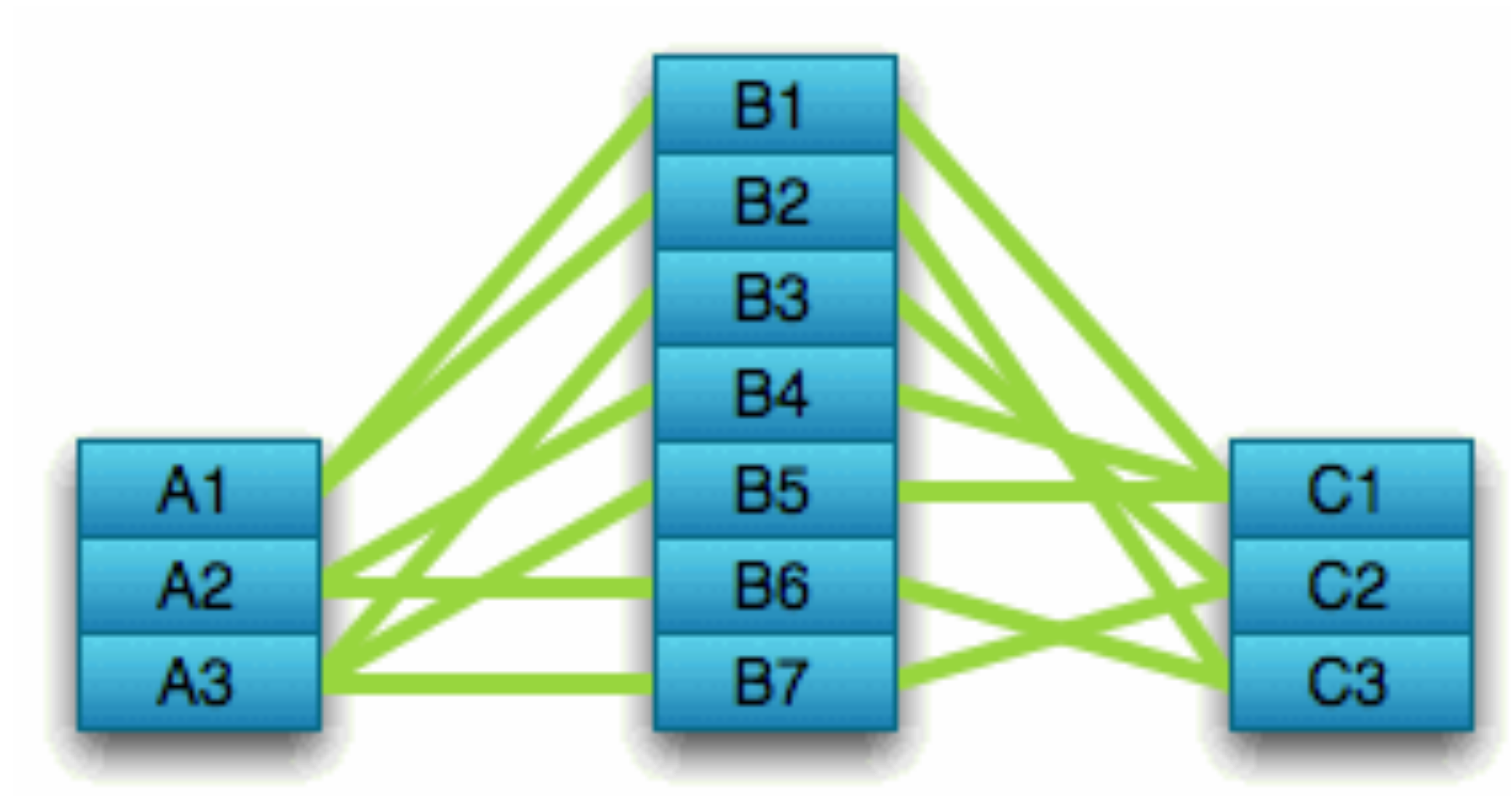
What is a Graph Database?

- A database with an explicit graph structure
- Each node knows its adjacent nodes
- As the number of nodes increases, the cost of a local step (or hop) remains the same
- Plus an Index for lookups

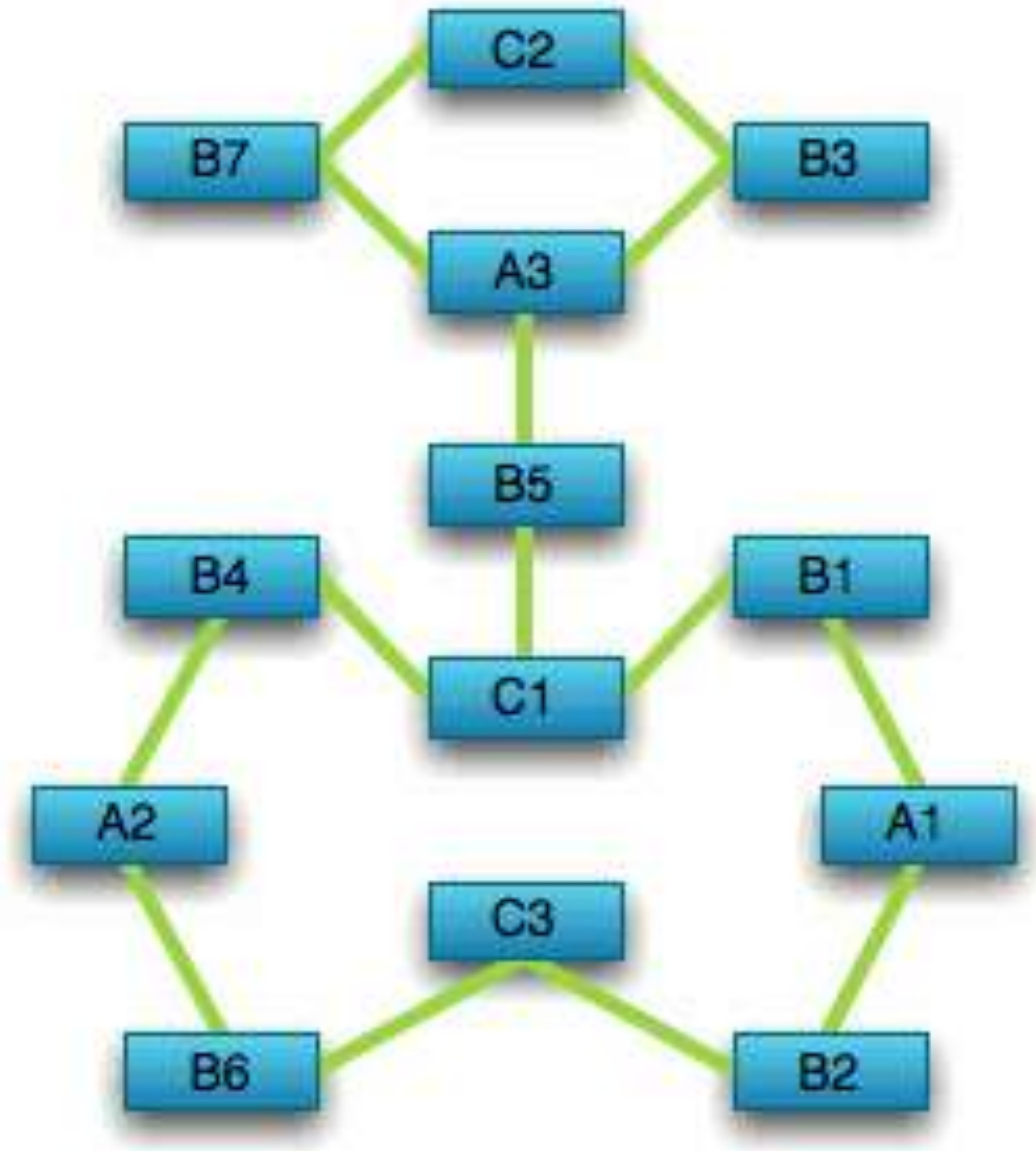
[M. De Marzi, 2012]

Graph Databases Compared to Relational Databases

Optimized for aggregation



Optimized for connections



[M. De Marzi, 2012]

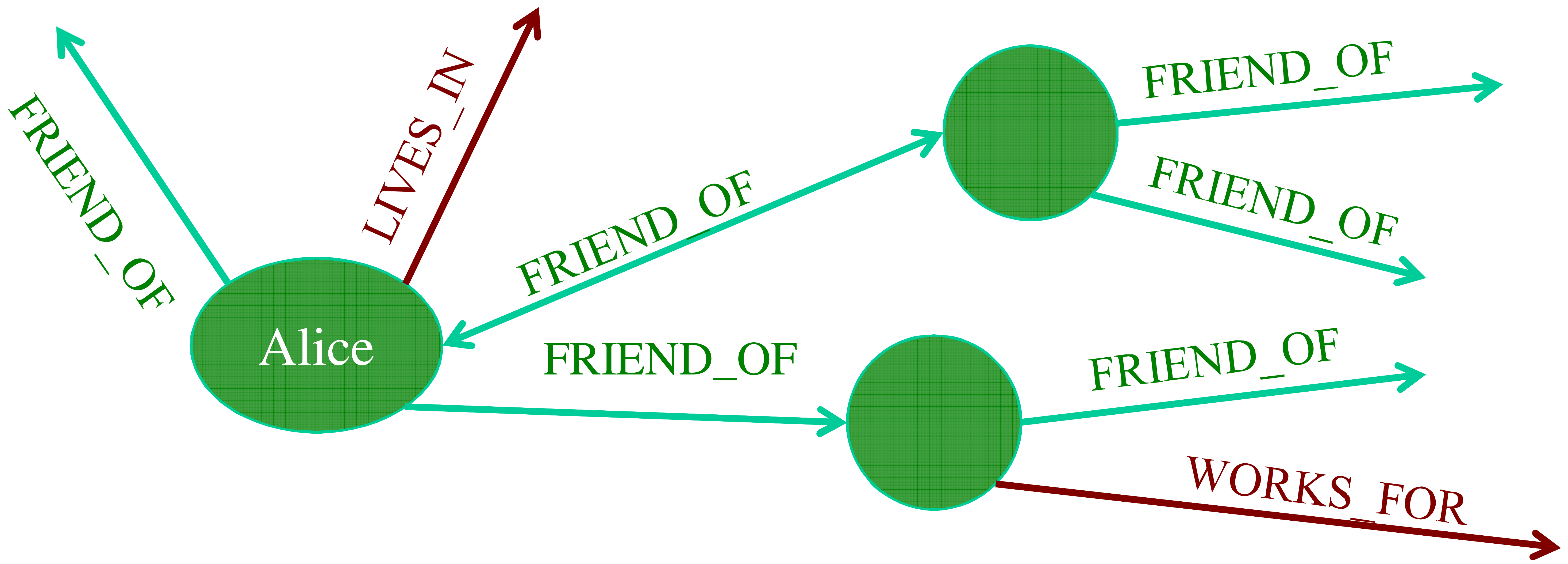
Graph Databases Compared to Relational Databases

- Relational Databases (querying is through joins)
  - In effect, the join operation forms a graph that is **dynamically constructed** as one table is linked to another table.
  - Must be inferred through a series of **index-intensive** operations
- Graph Databases (querying is through traversal paths)
  - There is no explicit join operation because vertices maintain **direct references** to their adjacent edges
  - Structures are "**hard-wired**", not computed at query time

[Rodriguez & Neubauer via Lembo & Rosati]

Example: Friend of Friends Query

- Relational:
- ```
SELECT p1.Person AS PERSON, p2.Person AS FRIEND_OF_FRIEND FROM
PersonFriend pf1 JOIN Person p1 ON
  pf1.PersonID = p1.ID JOIN PersonFriend pf2 ON
  pf2.PersonID = pf1.FriendID JOIN Person p2 ON
  pf2.FriendID = p2.ID
WHERE p1.Person = 'Alice' AND pf2.FriendID <> p1.ID
```
- Graph:

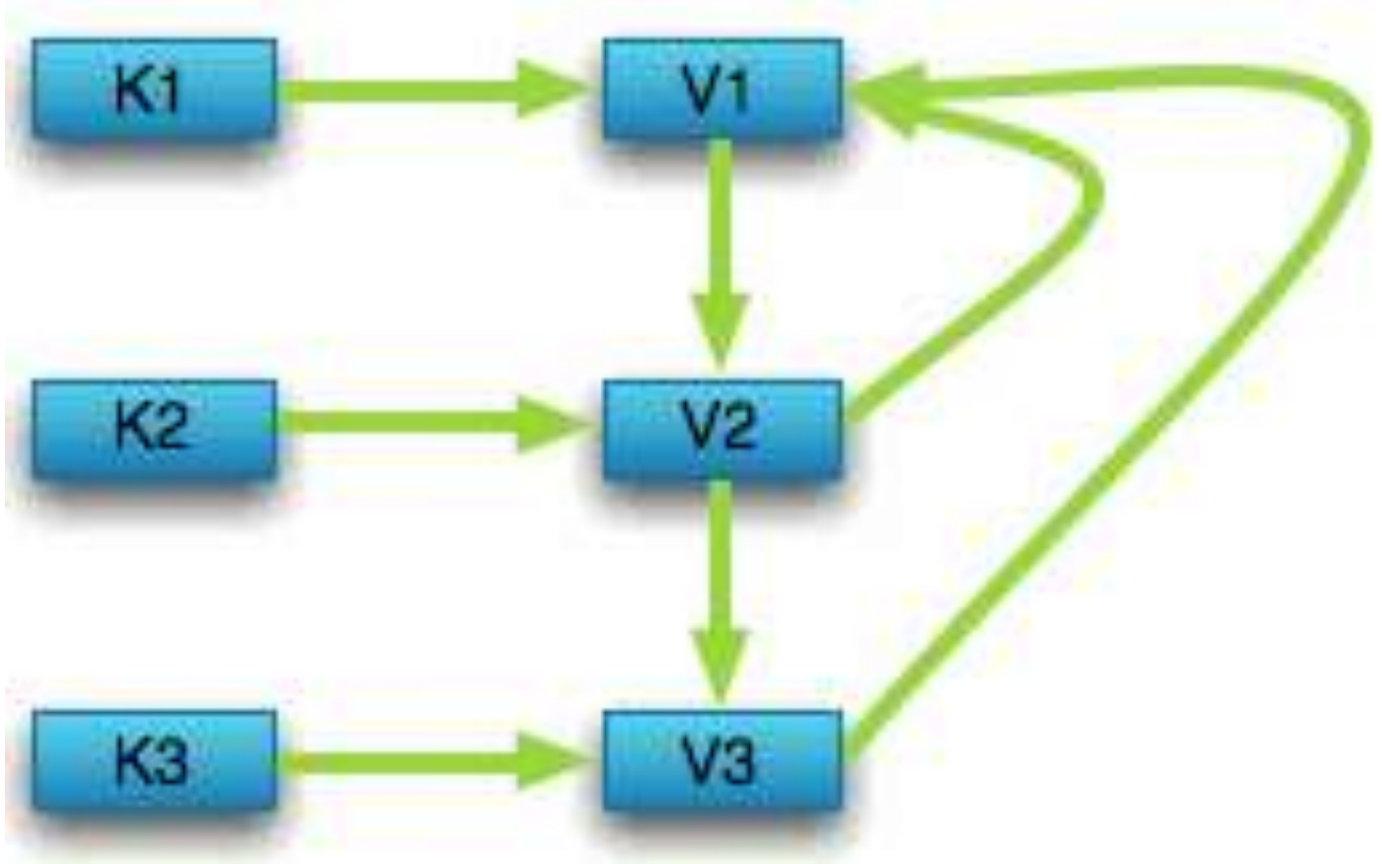



[Lembo & Rosati]
```

Graph Databases Compared to Key-Value Stores

Optimized for simple look-ups

Optimized for traversing connected data

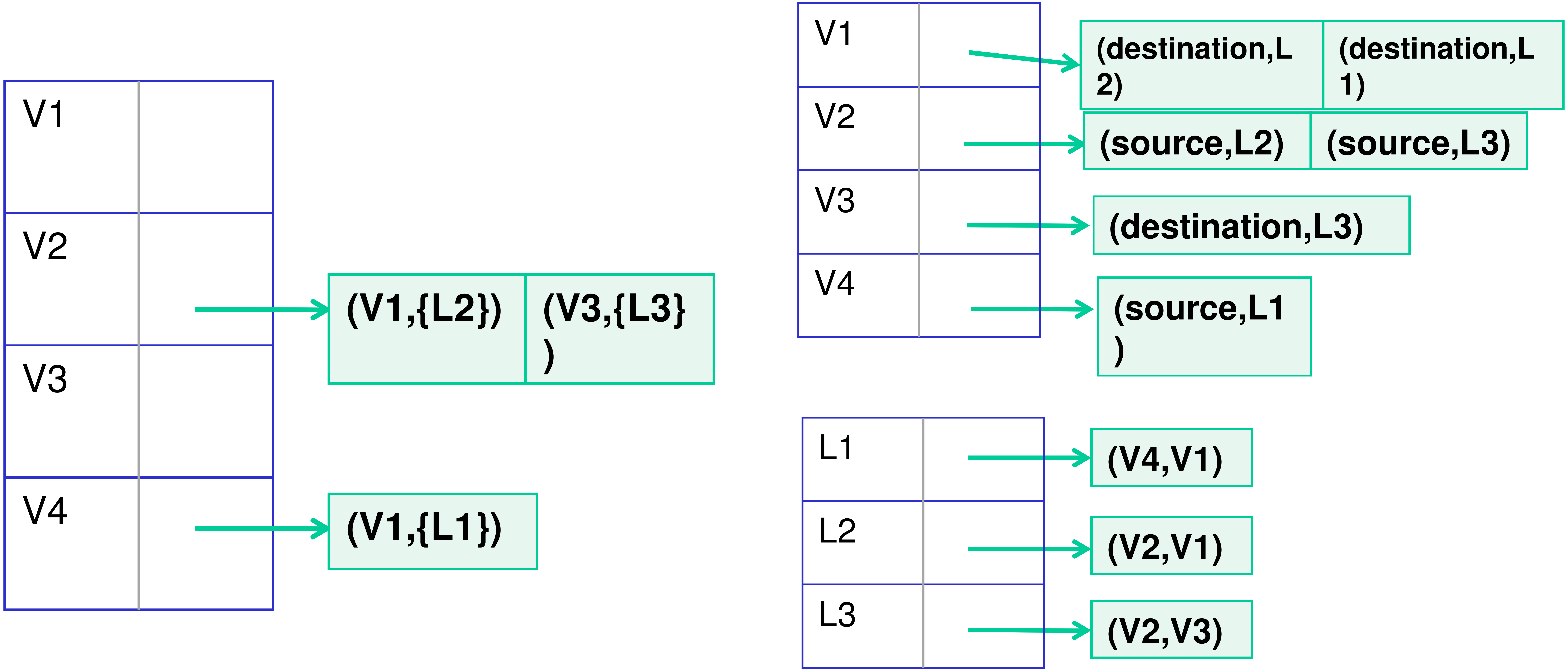


[M. De Marzi, 2012]

Storing and Traversing Graphs

- Storage:
  - Adjacency List: nodes store their neighbors
  - Incidence List: nodes store edges and edges store incident nodes
  - Adjacency Matrix: adjacency list in matrix form (rows & cols are nodes)
  - Incidence Matrix: rows are vertices, columns are **edges**
- Traversal:
  - Breadth-first Search
  - Depth-first Search

Adjacency List vs. Incidence List



[Acosta et al.]

Adjacency Matrix vs. Incidence Matrix

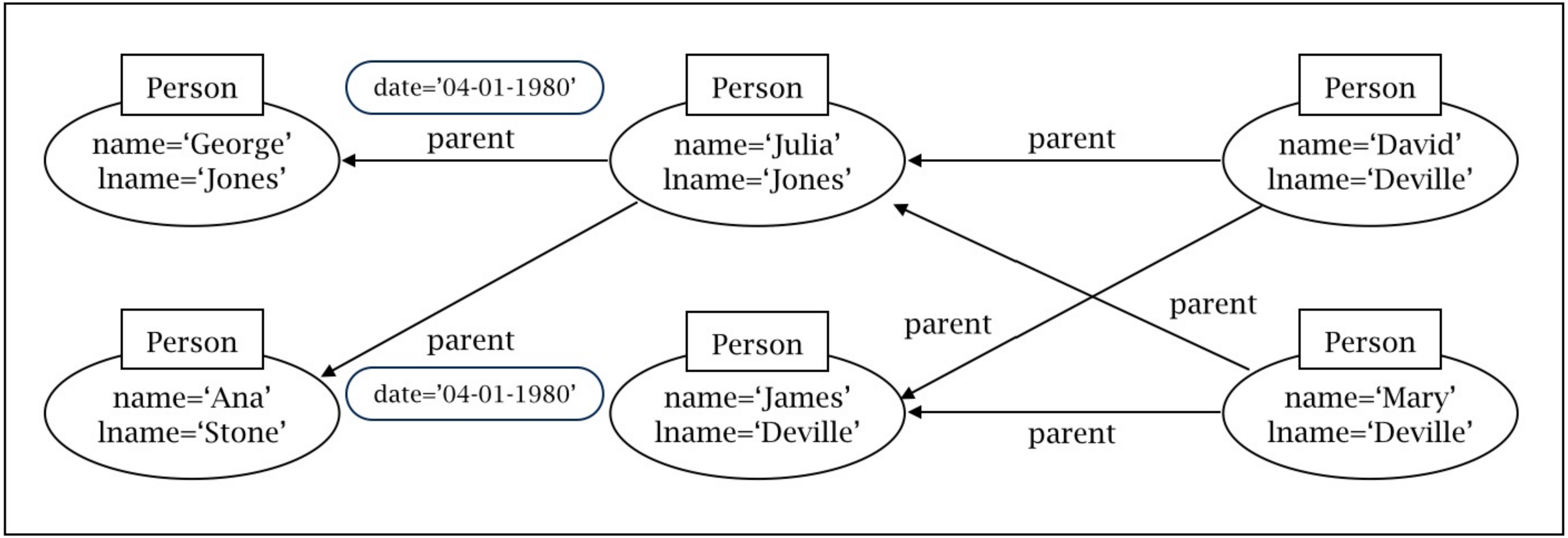
	V1	V2	V3	V4
V1				
V2	{L2}		{L3}	
V3				
V4	{L1}			

	L1	L2	L3
V1	destination	destination	
V2		source	source
V3			destination
V4	source		

[Acosta et al.]

Property Graph Model (Cypher in neo4j)

- Directed, labelled, attributed multigraph
- Properties are **key/value pairs** that represent metadata for nodes and edges



[R. Angles and C. Gutierrez, 2017]

Graph Query Languages: Cypher

- Implemented by neo4j system
- Expresses reachability queries via path expressions
  - `p = (a)-[:knows*]->(b)`: nodes from `a` to `b` following `knows` edges
- ```
  START x=node:person(name="John")
  MATCH (x)-[:friend]->(y)
  RETURN y.name
  ```

[R. Angles and C. Gutierrez, 2017]
  ```

Graph DBMS Building Blocks

●->●
property graph data model

graph query language

graph visualization

subgraph matching

relational queries

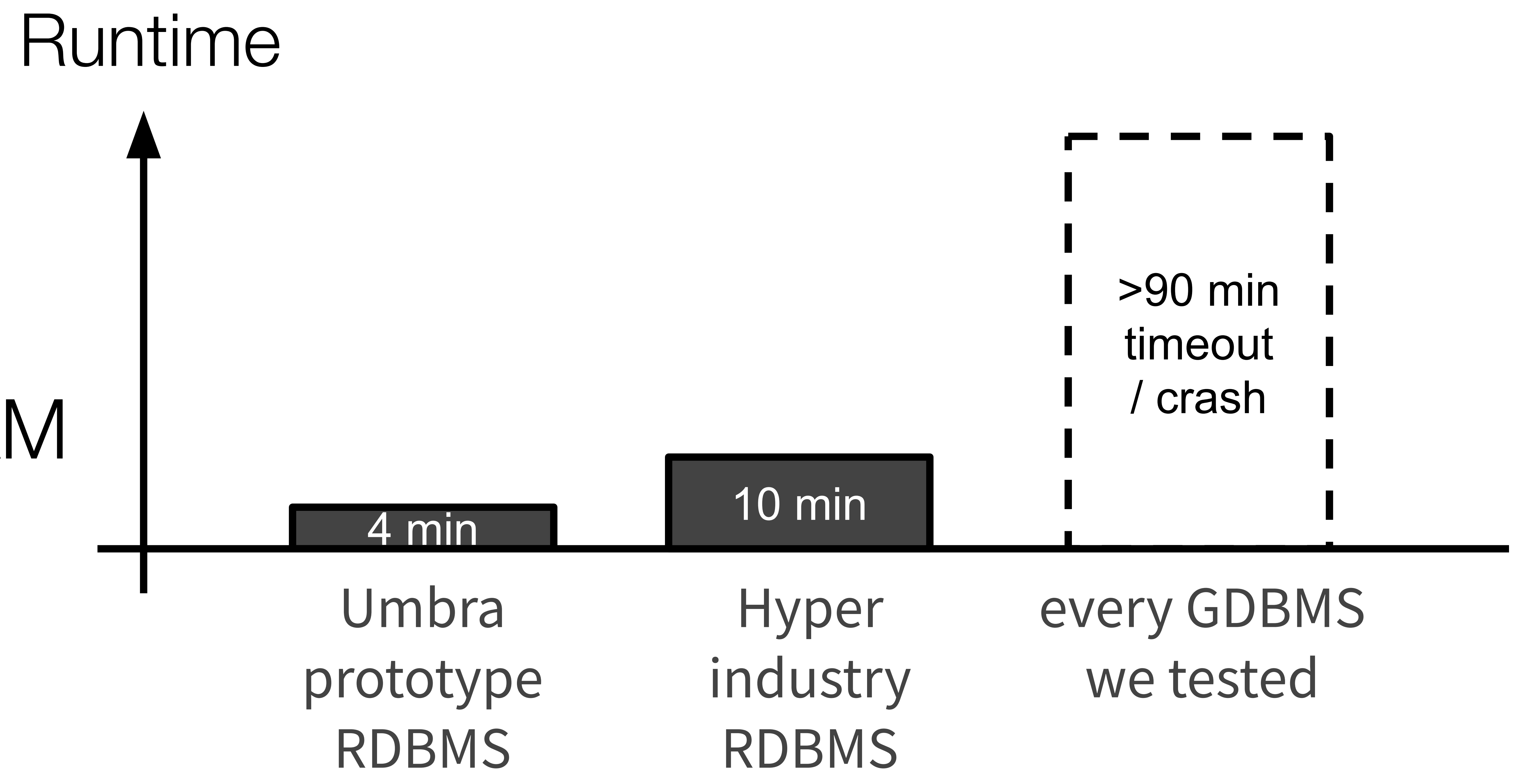
path queries

stored procedures

[P. Boncz, 2022]

Graph DBMS Problems

- performance
  - Slow loading speeds
  - Query speeds over magnitude slower than RDBMS
- scalability
  - Low datasize limit, typically << RAM
  - Little benefit from parallelism
- reliability
  - Loads never terminate
  - Query run out of memory or crash
  - Bugs



[P. Boncz, 2022]

Quiz Monday

- Read Beast paper
- Quiz at the beginning of class

Assignment 5

- Last assignment, coming soon
- Graphs, visualization, spatial data, time series

Data Exploration through Visualization

Transportation Data - NYC MTA

MTA Fare Data Exploration

	REMOTE	STATION	FF ▼	SEN/DIS	7-D AFAS UNL	D AFAS/RMF I	JOINT RR TKT	7-D UNL	30-D UNL
1	R011	42ND STREET & 8TH AVENUE	00228985	00008471	00000441	00001455	00000134	00033341	00071255
2	R170	14TH STREET-UNION SQUARE	00224603	00011051	00000827	00003026	00000660	00089367	00199841
3	R046	42ND STREET & GRAND CENTRAL	00207758	00007908	00000323	00001183	00003001	00040759	00096613
4	R012	34TH STREET & 8TH AVENUE	00188311	00006490	00000498	00001279	00003622	00035527	00067483
5	R293	34TH STREET - PENN STATION	00168768	00006155	00000523	00001065	00005031	00030645	00054376
6	R033	42ND STREET/TIMES SQUARE	00159382	00005945	00000378	00001205	00000690	00058931	00078644
7	R022	34TH STREET & 6TH AVENUE	00156008	00006276	00000487	00001543	00000712	00058910	00110466
8	R084	59TH STREET/COLUMBUS CIRCLE	00155262	00009484	00000589	00002071	00000542	00053397	00113966
9	R020	47-50 STREETS/ROCKEFELLER	00143500	00006402	00000384	00001159	00000723	00037978	00090745
10	R179	86TH STREET-LEXINGTON AVE	00142169	00010367	00000470	00001839	00000271	00050328	00125250
11	R023	34TH STREET & 6TH AVENUE	00134052	00005005	00000348	00001112	00000649	00031531	00075040
12	R029	PARK PLACE	00121614	00004311	00000287	00000931	00000792	00025404	00065362
13	R047	42ND STREET & GRAND CENTRAL	00100742	00004273	00000185	00000704	00001241	00022808	00068216

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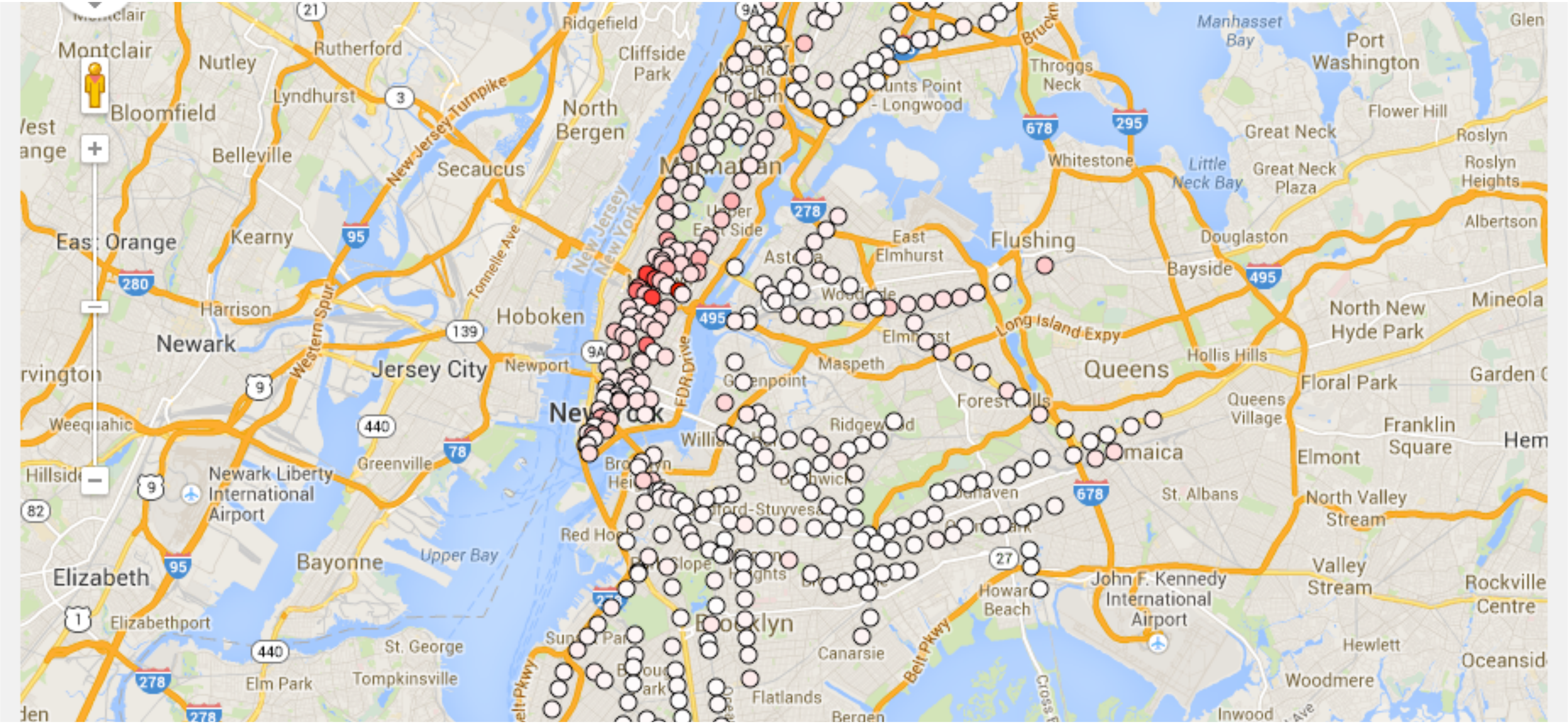

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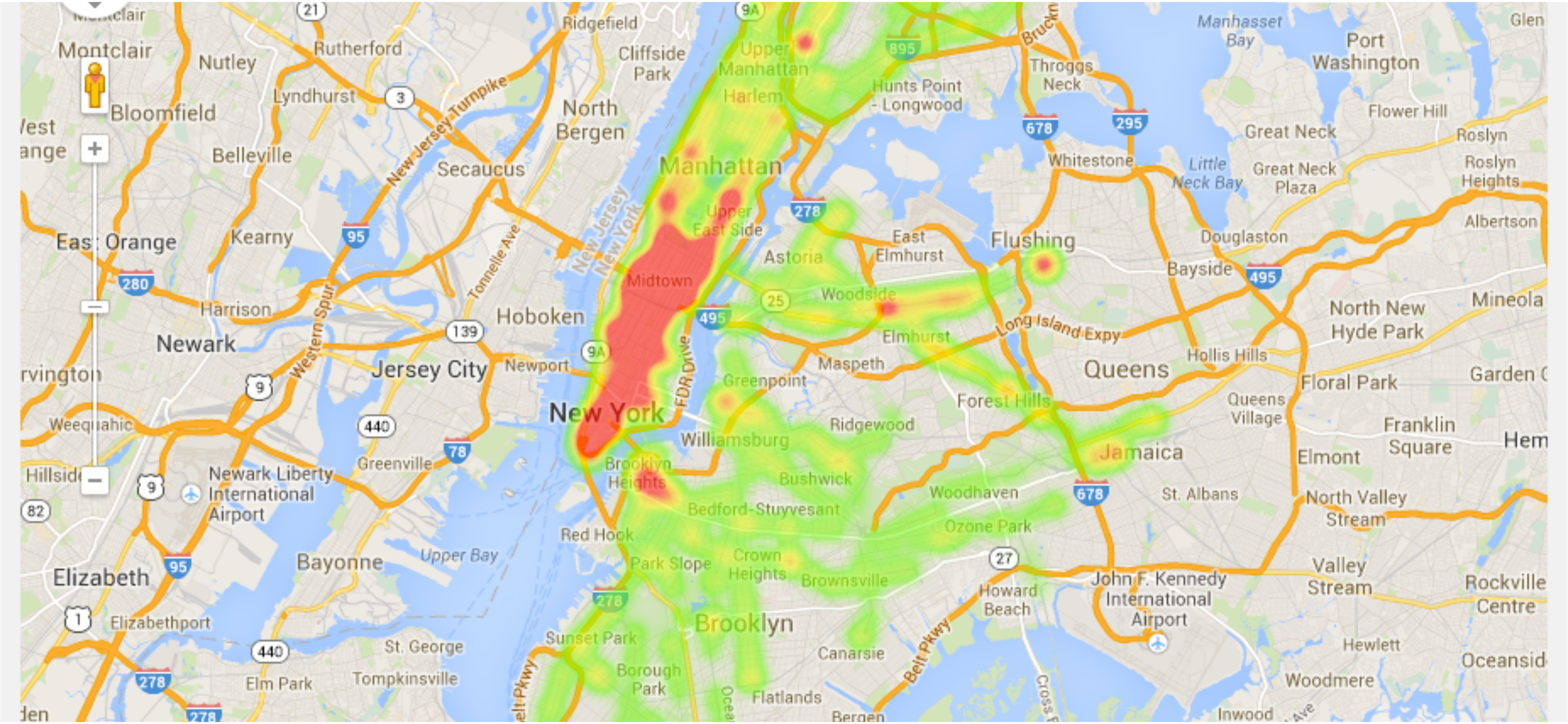

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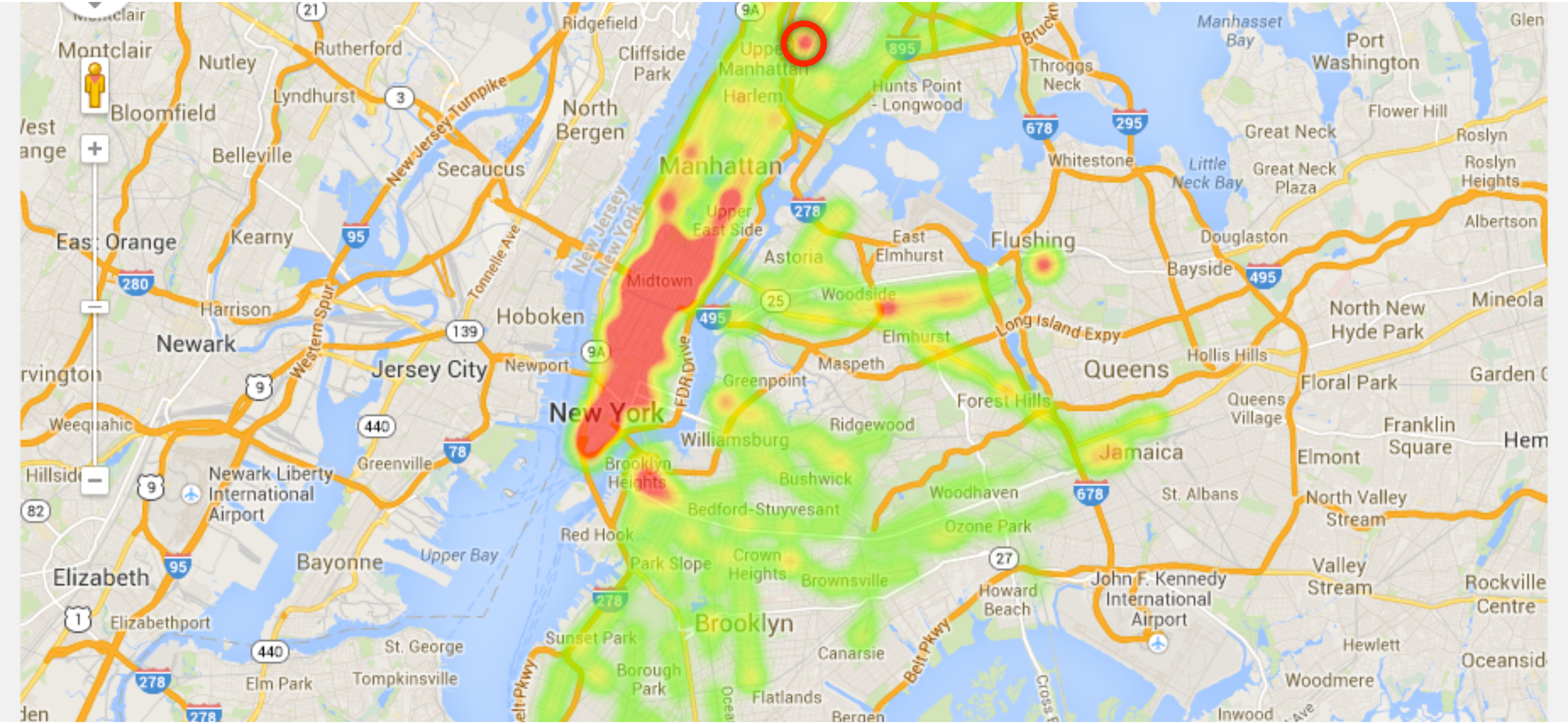

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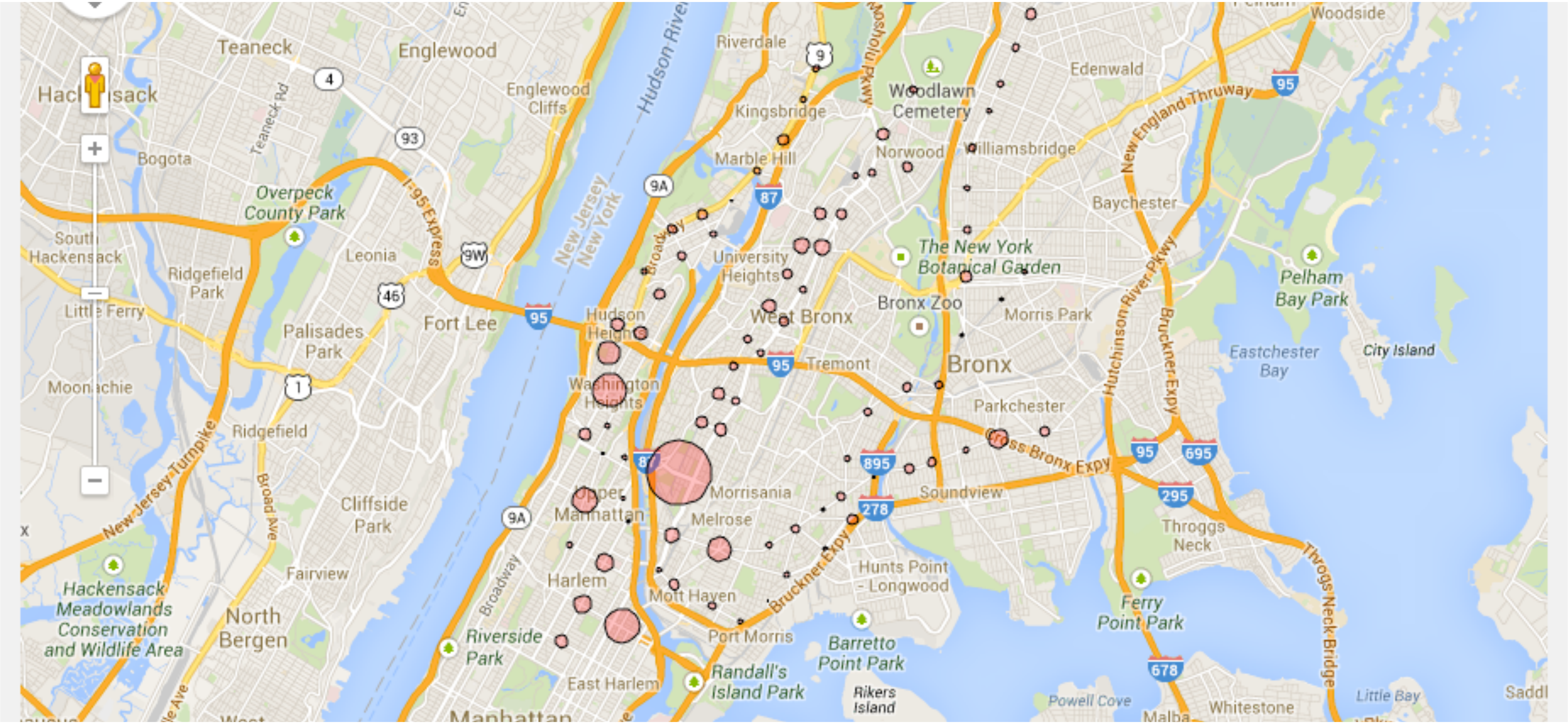

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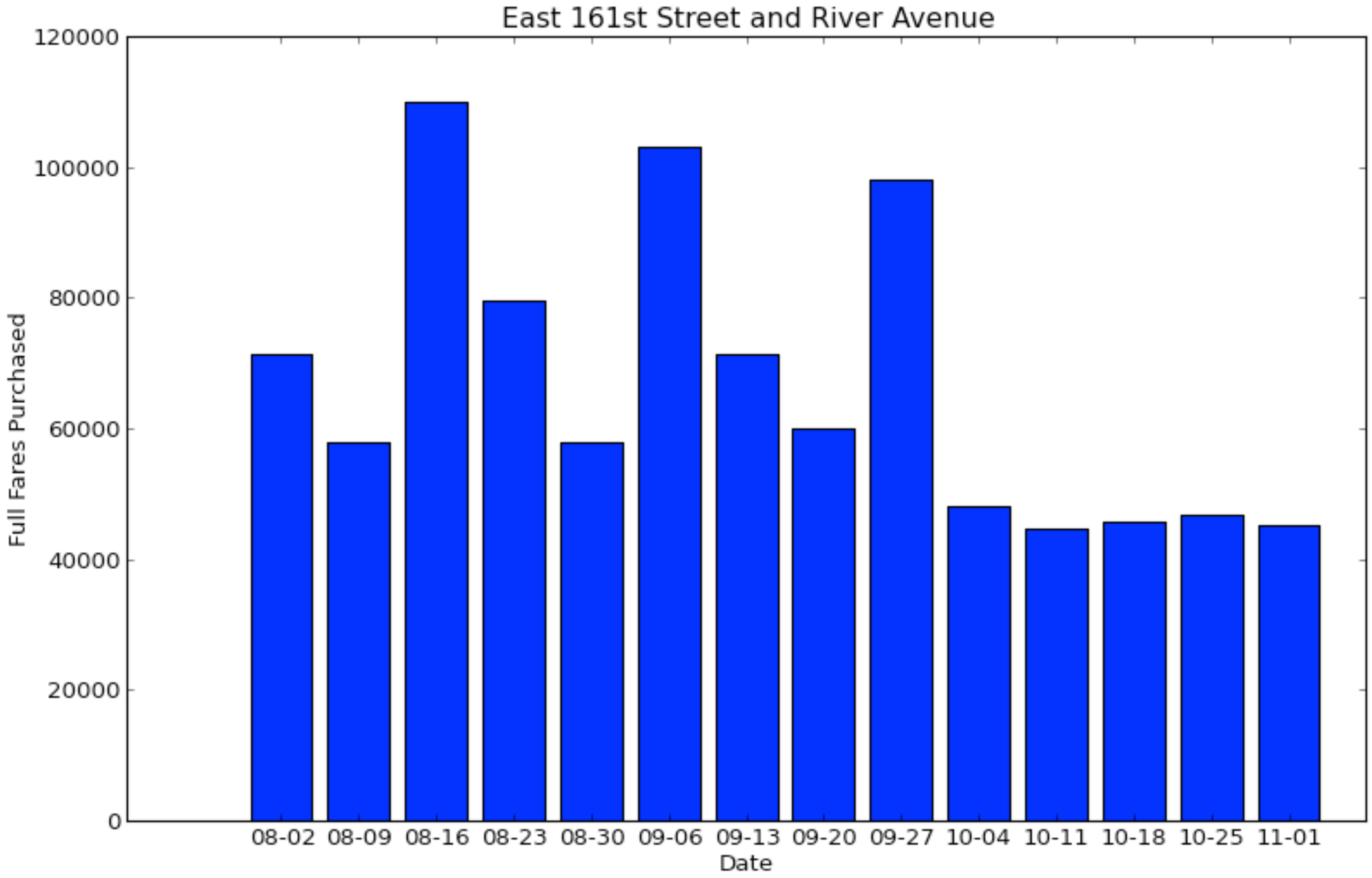

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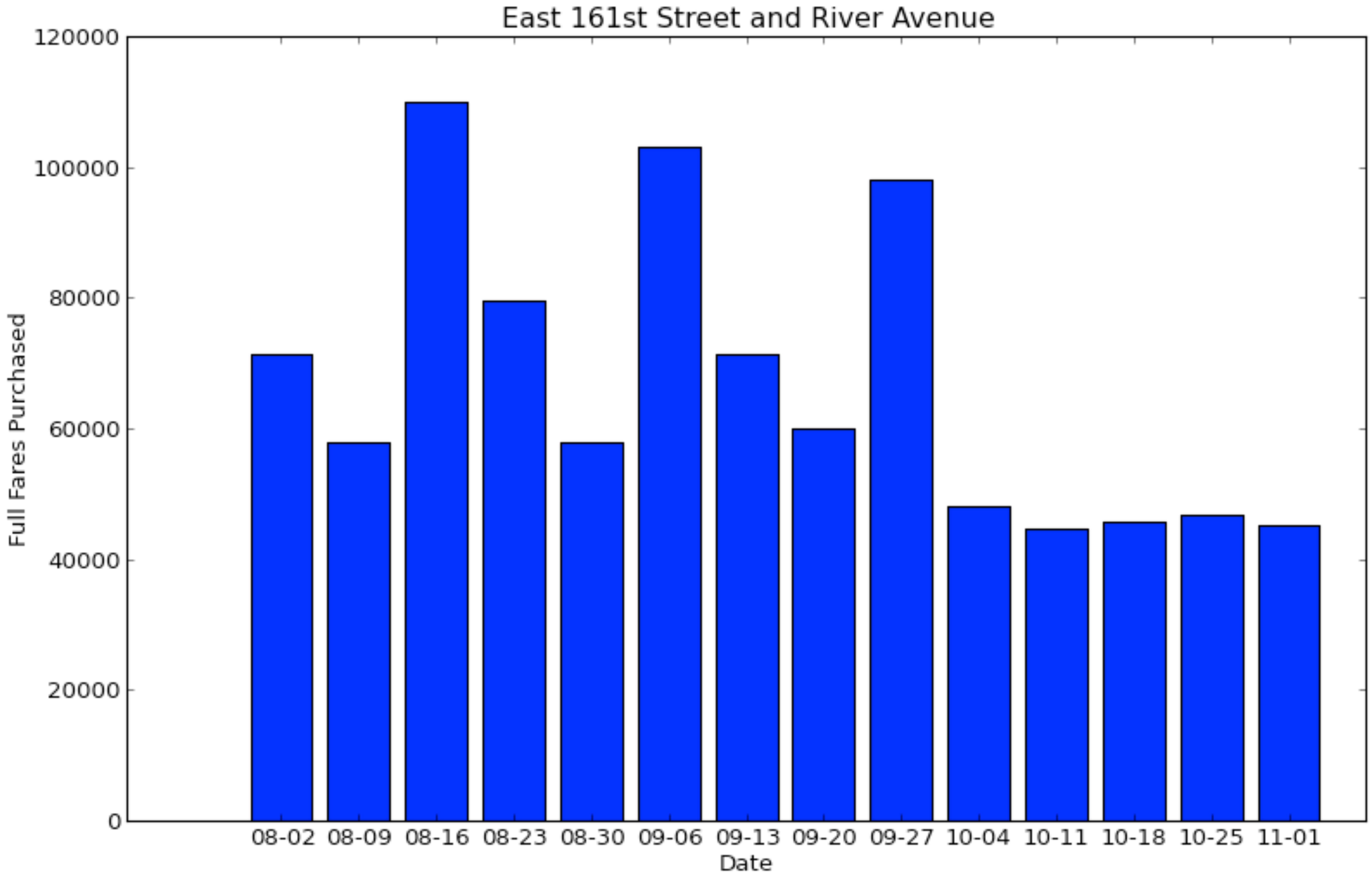
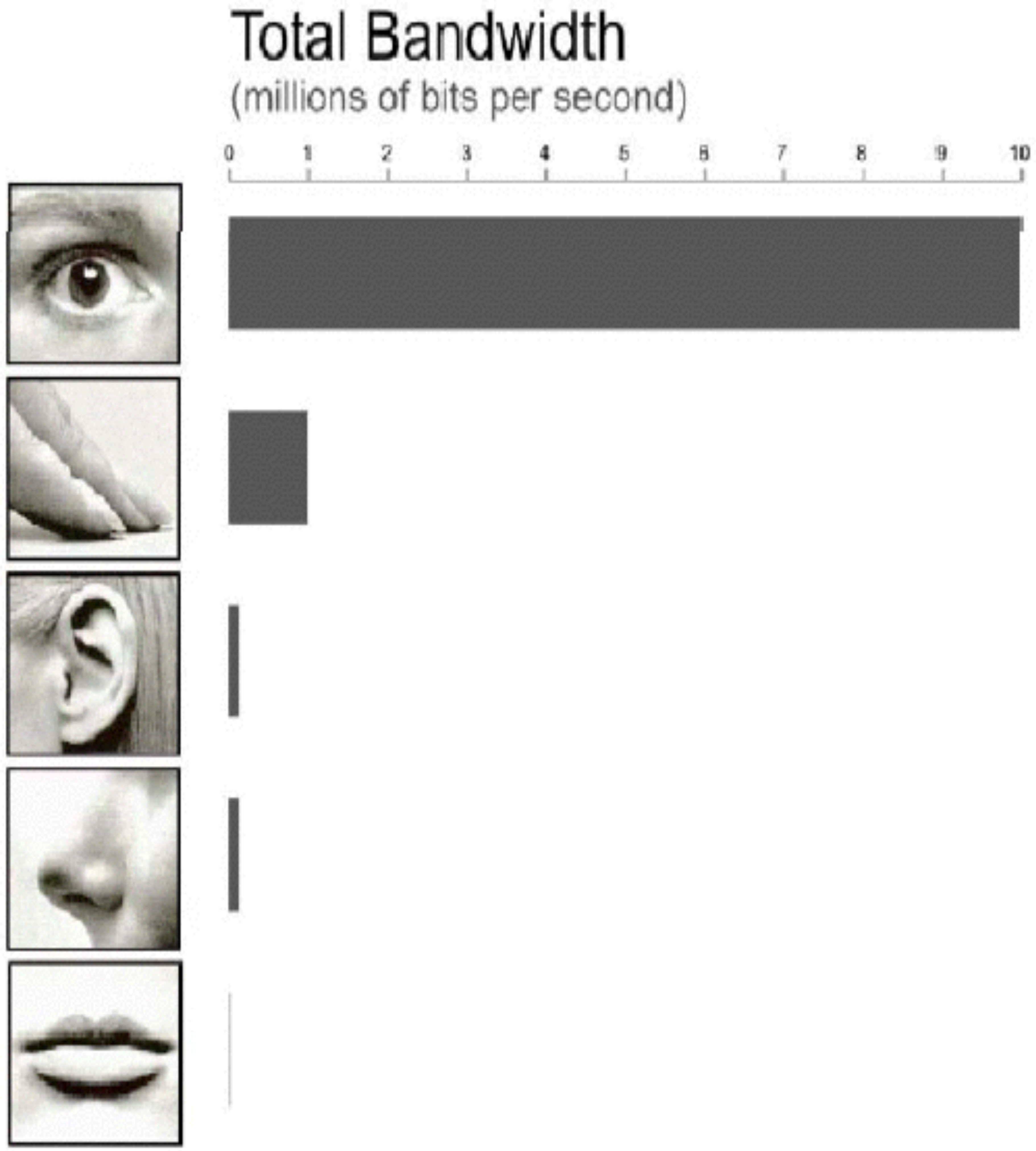


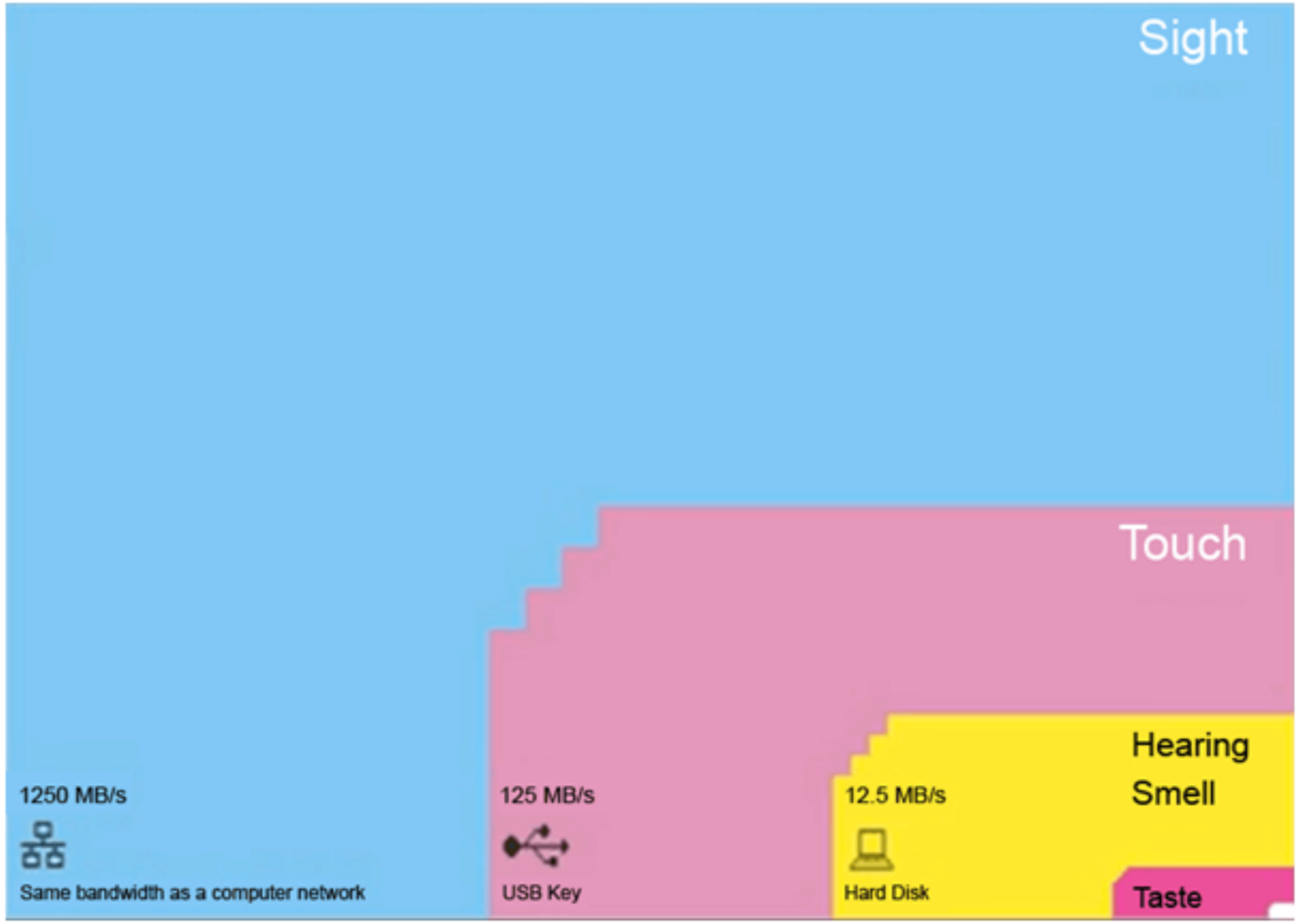
Definition of Visualization

"Computer-based visualization systems provide visual representations of datasets designed to help people carry out tasks more effectively" — T. Munzner

Why do we visualize data?



[via A. Lex]



[T. Nørretranders]

Why Visual?

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

[F. J. Anscombe]

Why Visual?

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

Mean of x	9
Variance of x	11
Mean of y	7.50
Variance of y	4.122
Correlation	0.816

[F. J. Anscombe]

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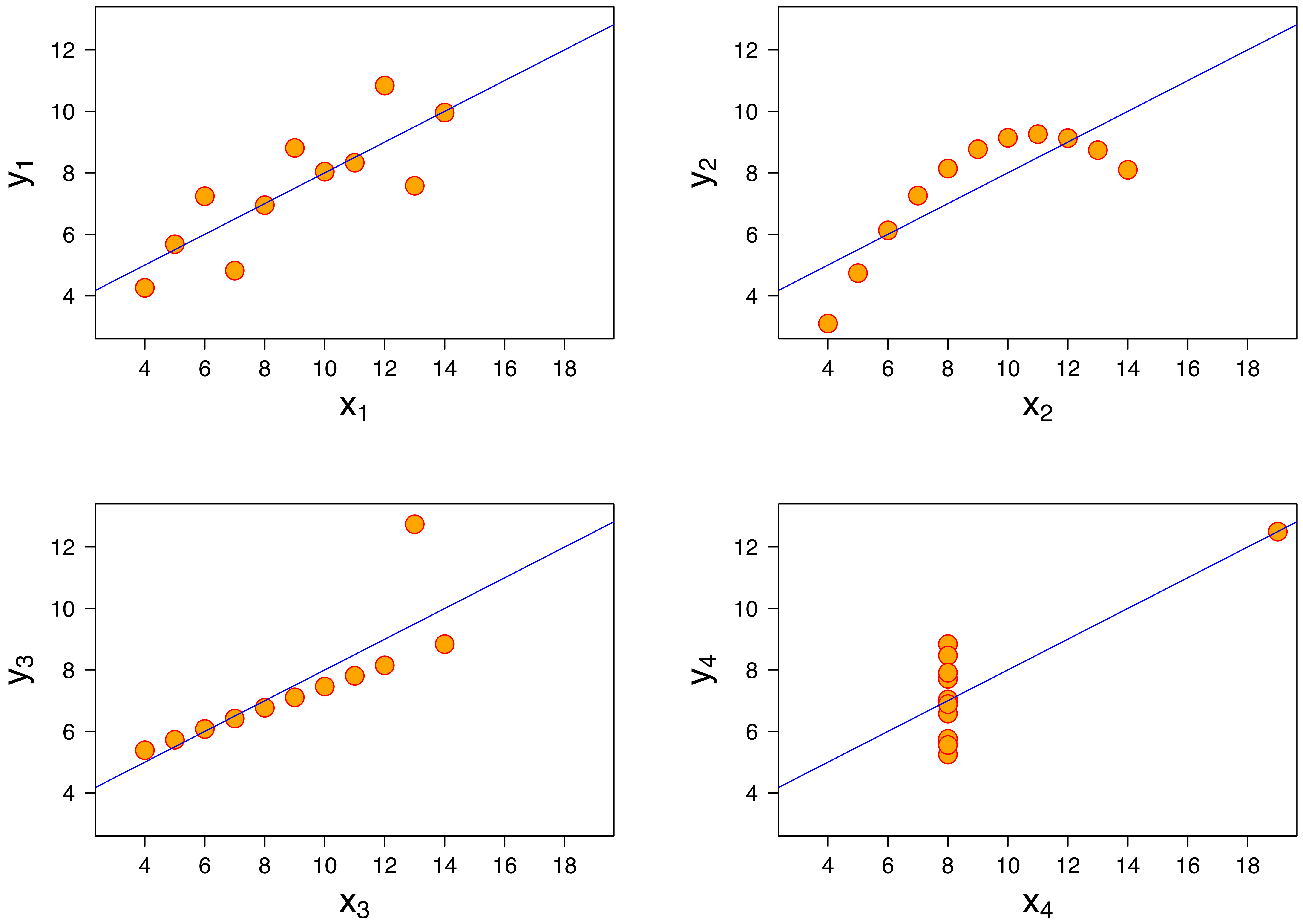

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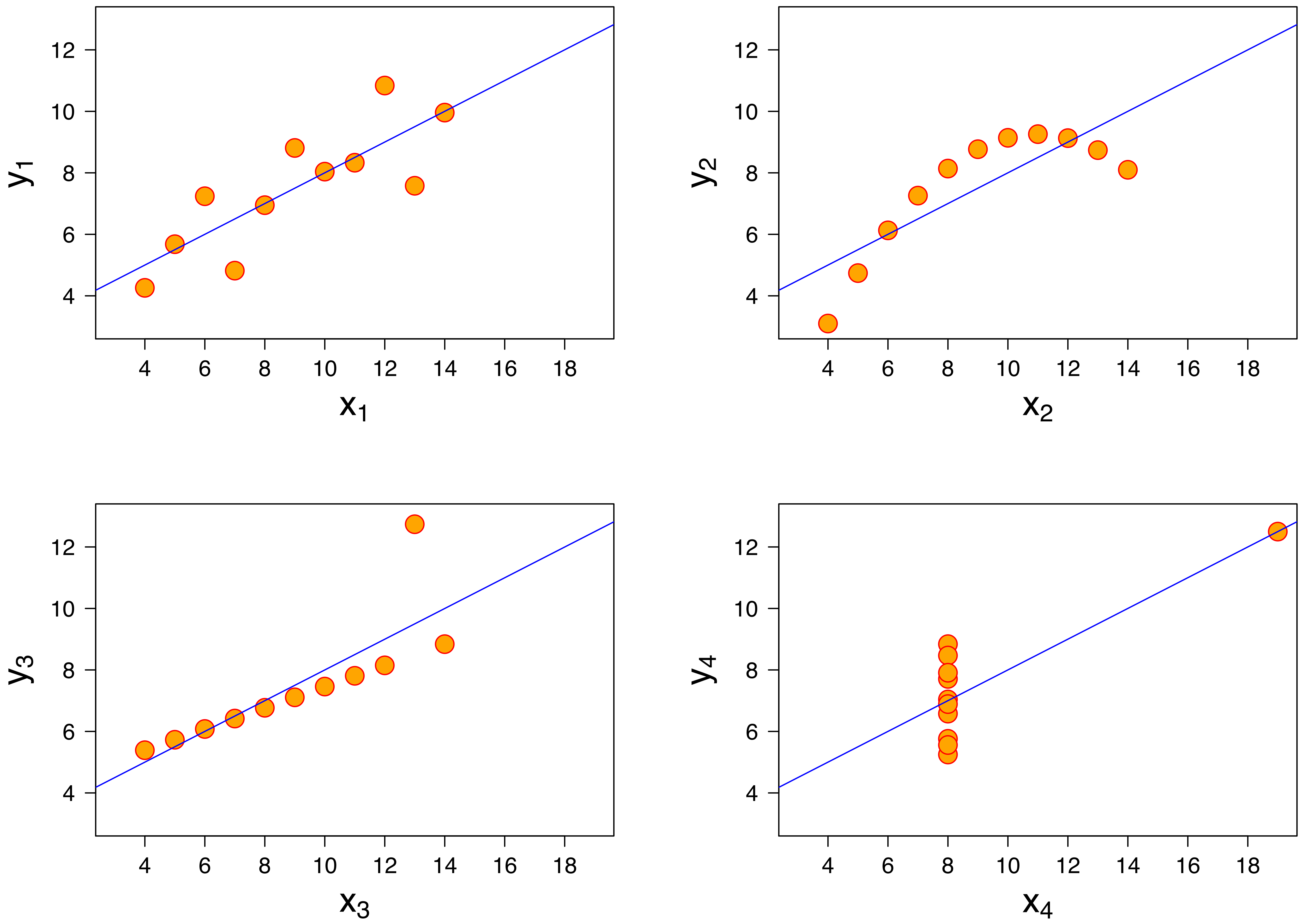

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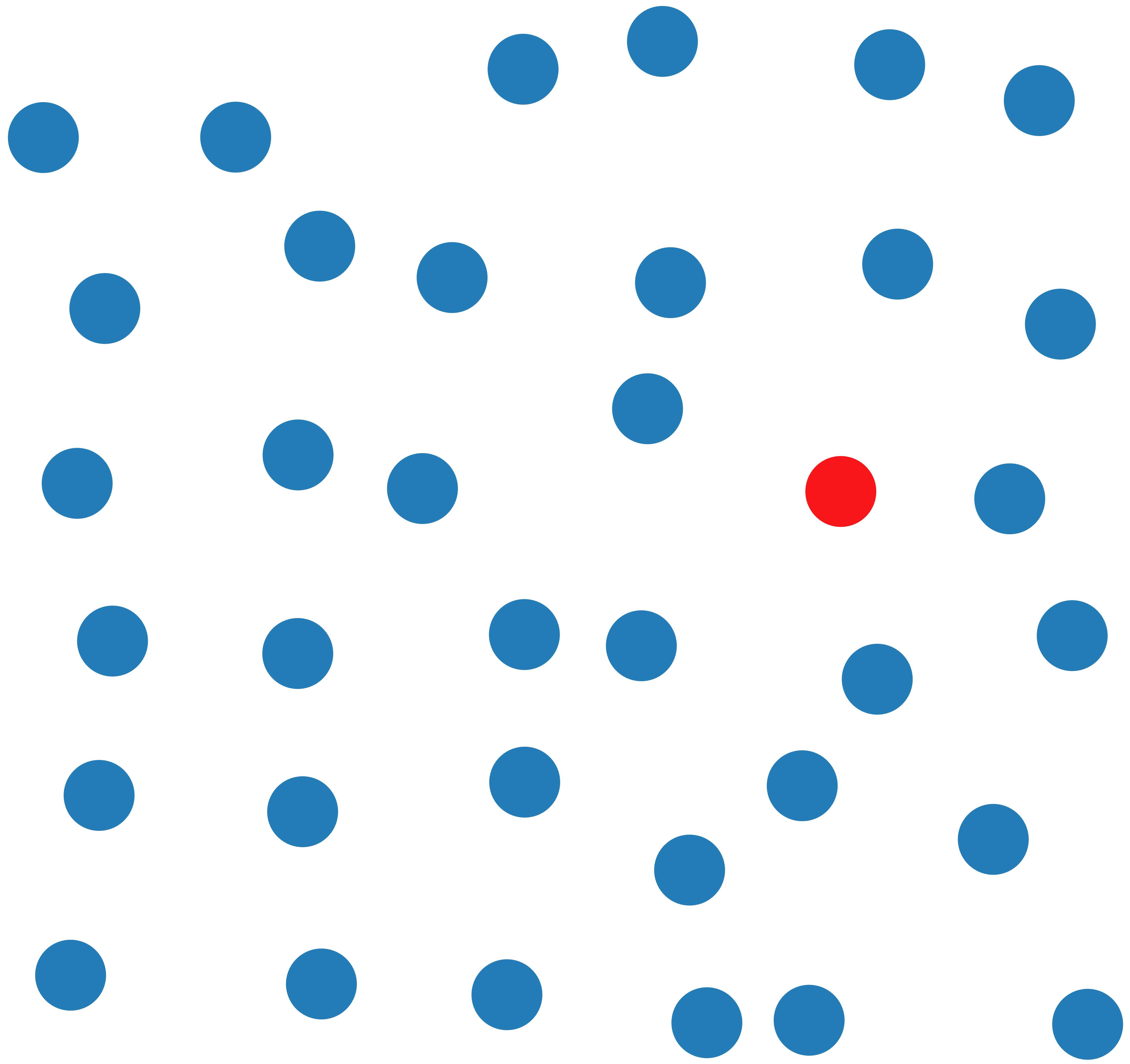
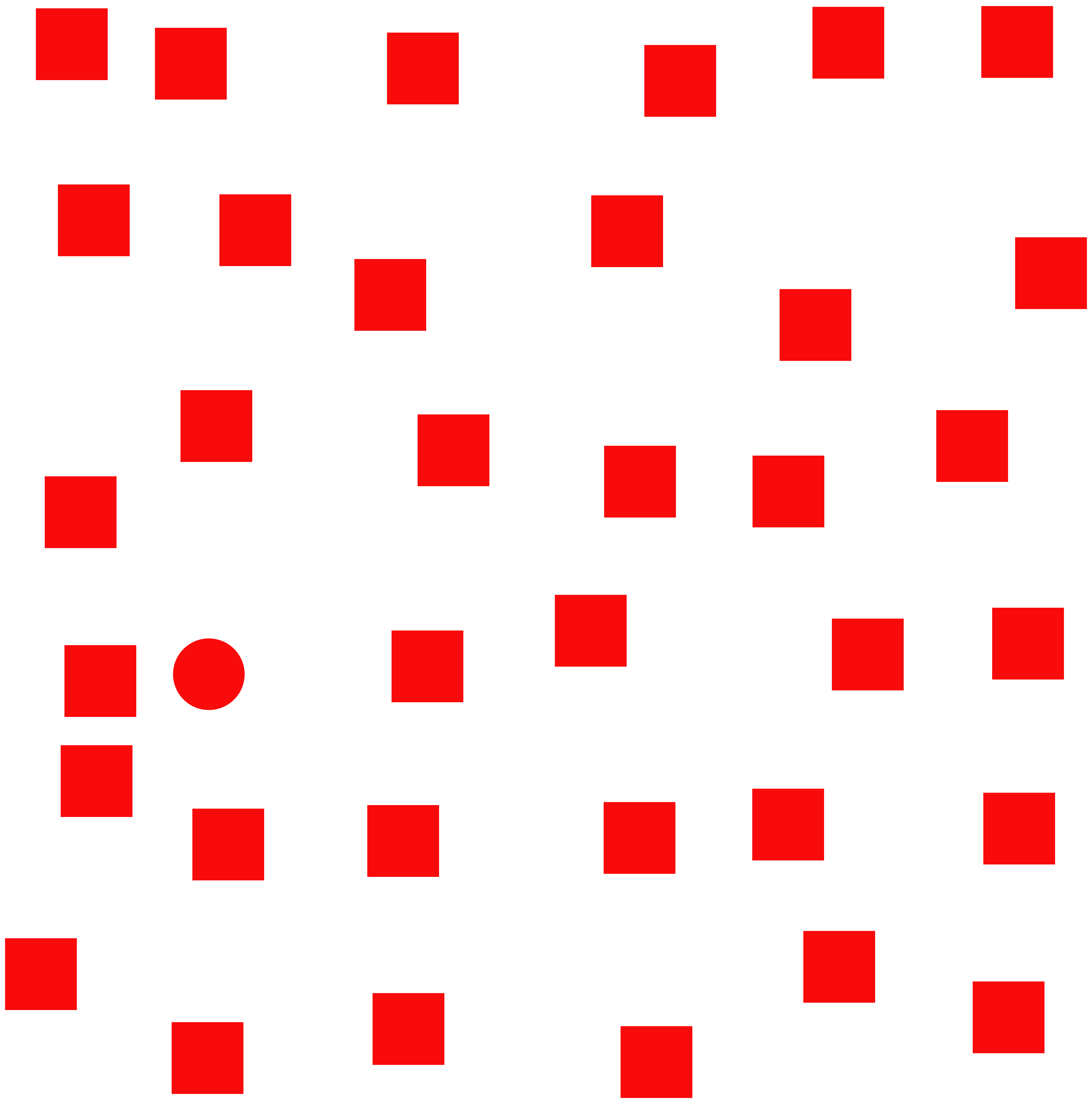
[F. J. Anscombe]

Visual Pop-out



[C. G. Healey]

Visual Pop-out



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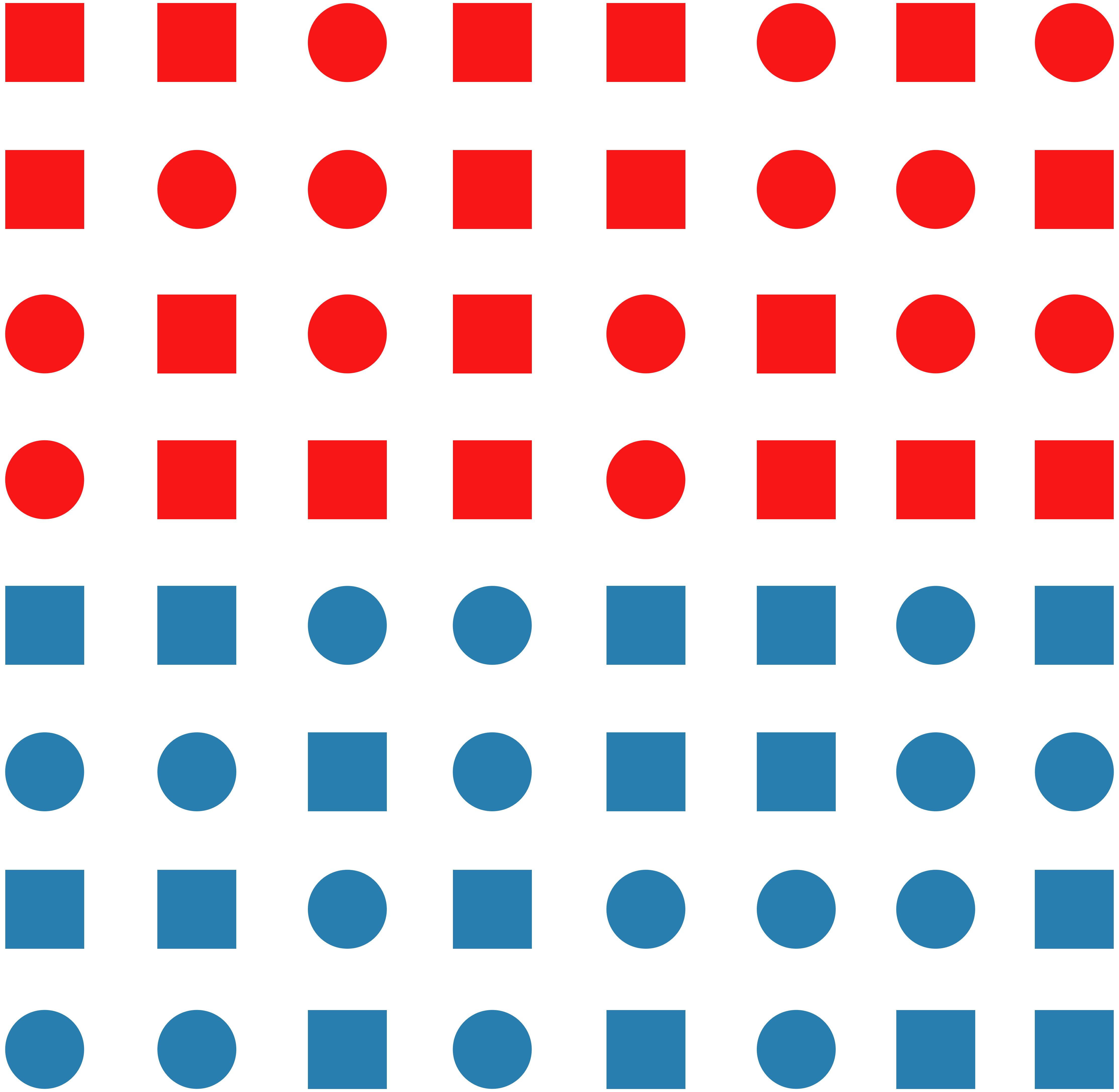
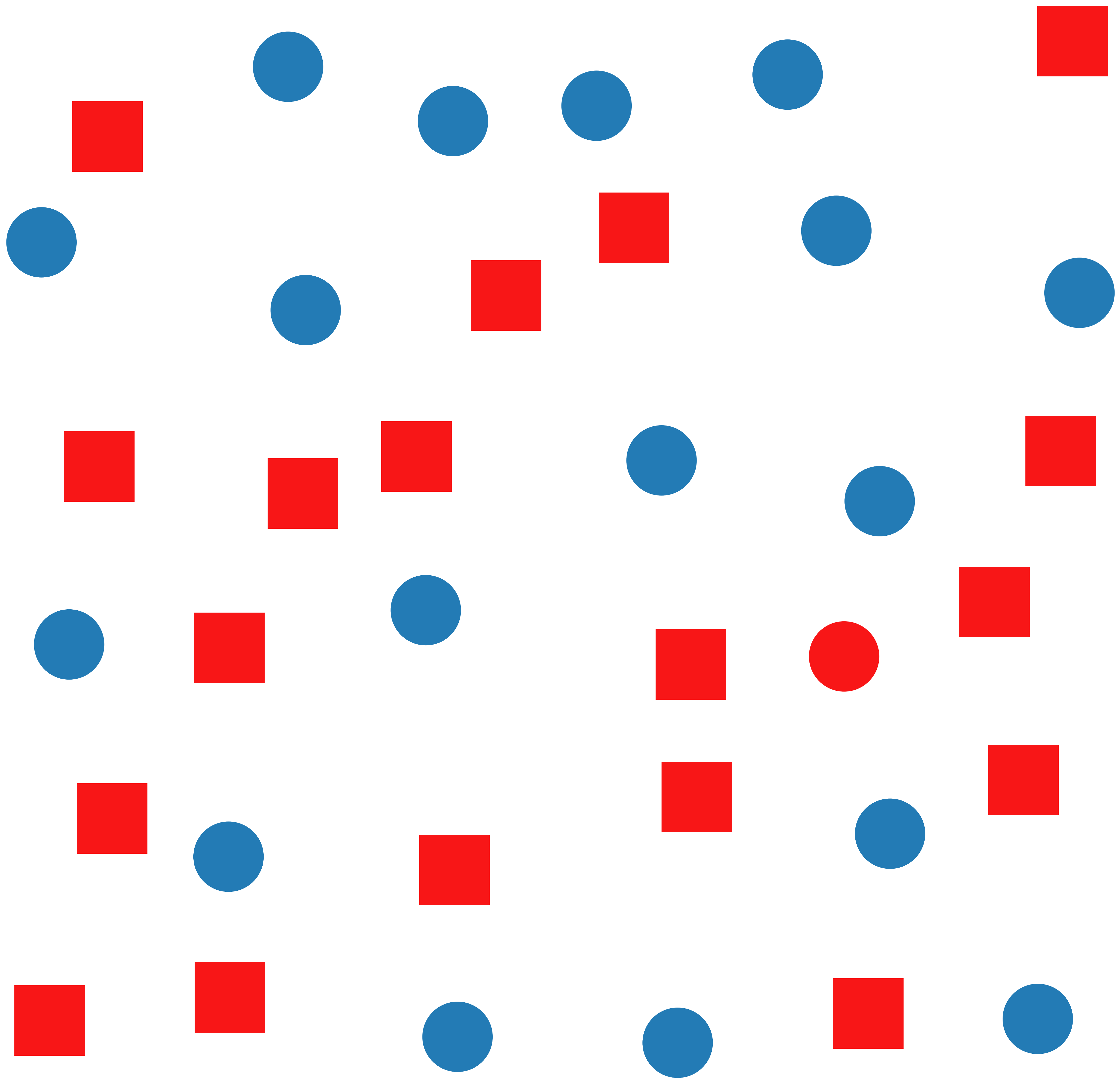


[C. G. Healey]

Visual Perception Limitations



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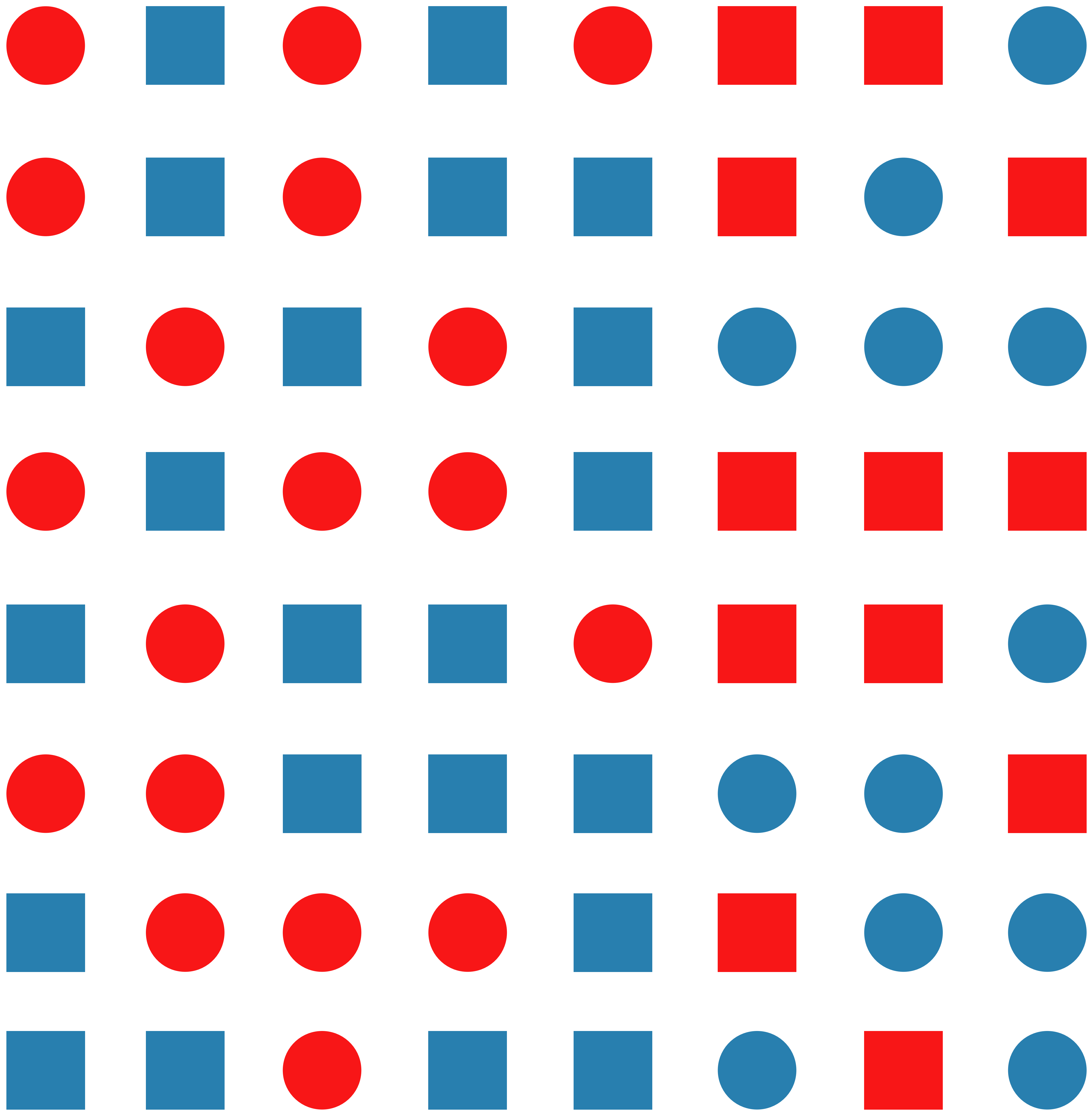

[C. G. Healey]

Databases and Visualization?

Scalable Visualization

J. Heer