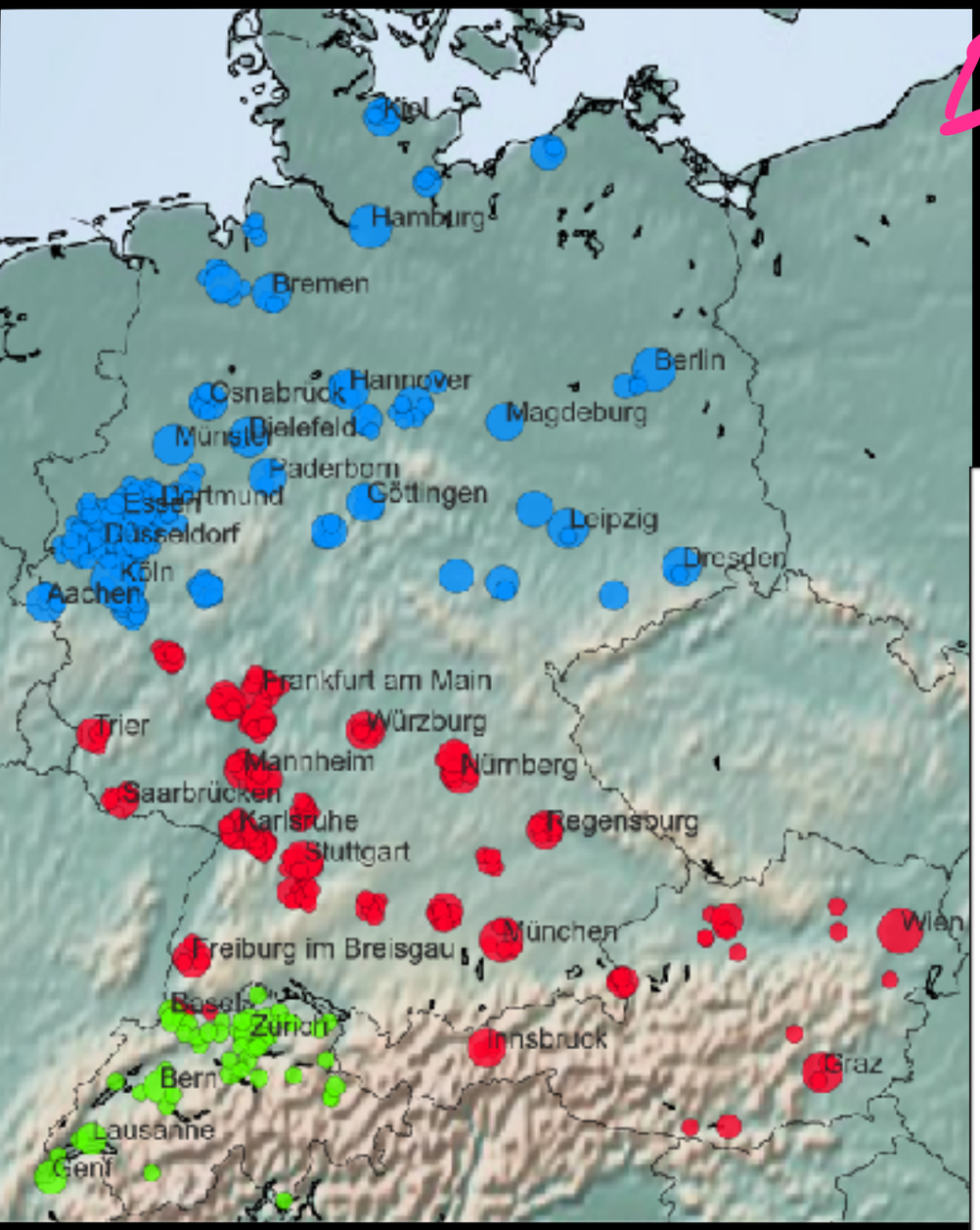
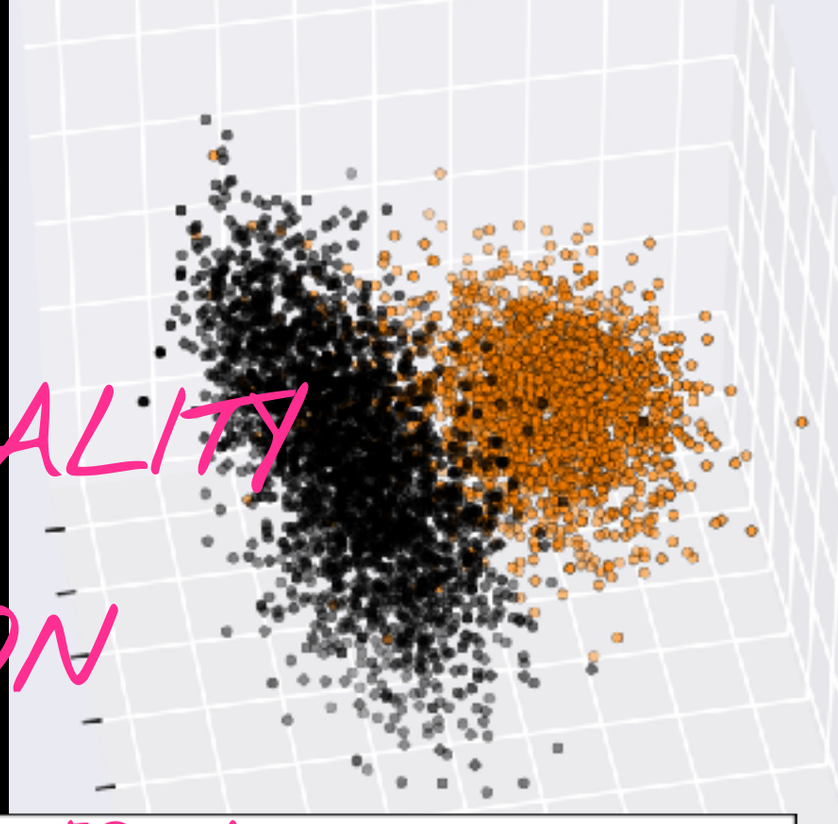
Examples

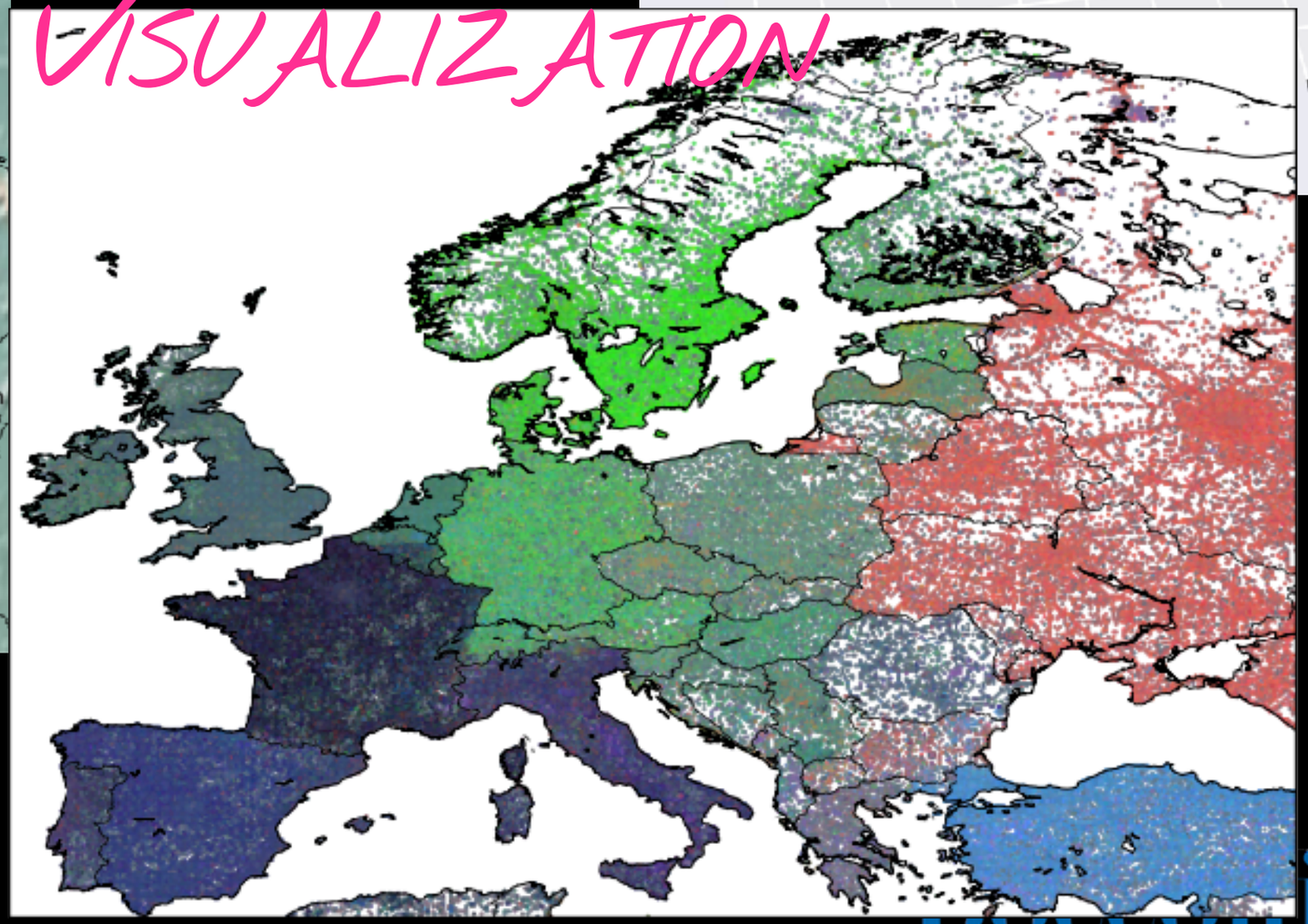


Clustering



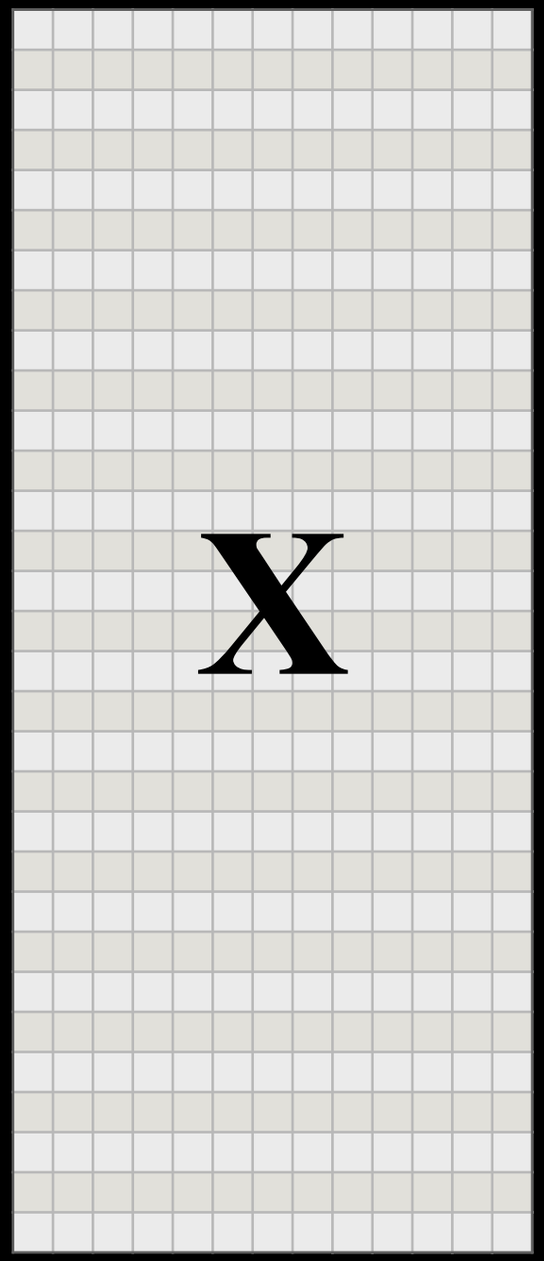
Dimensionality Reduction

Visualization



Latent Dimensions

Data Matrix

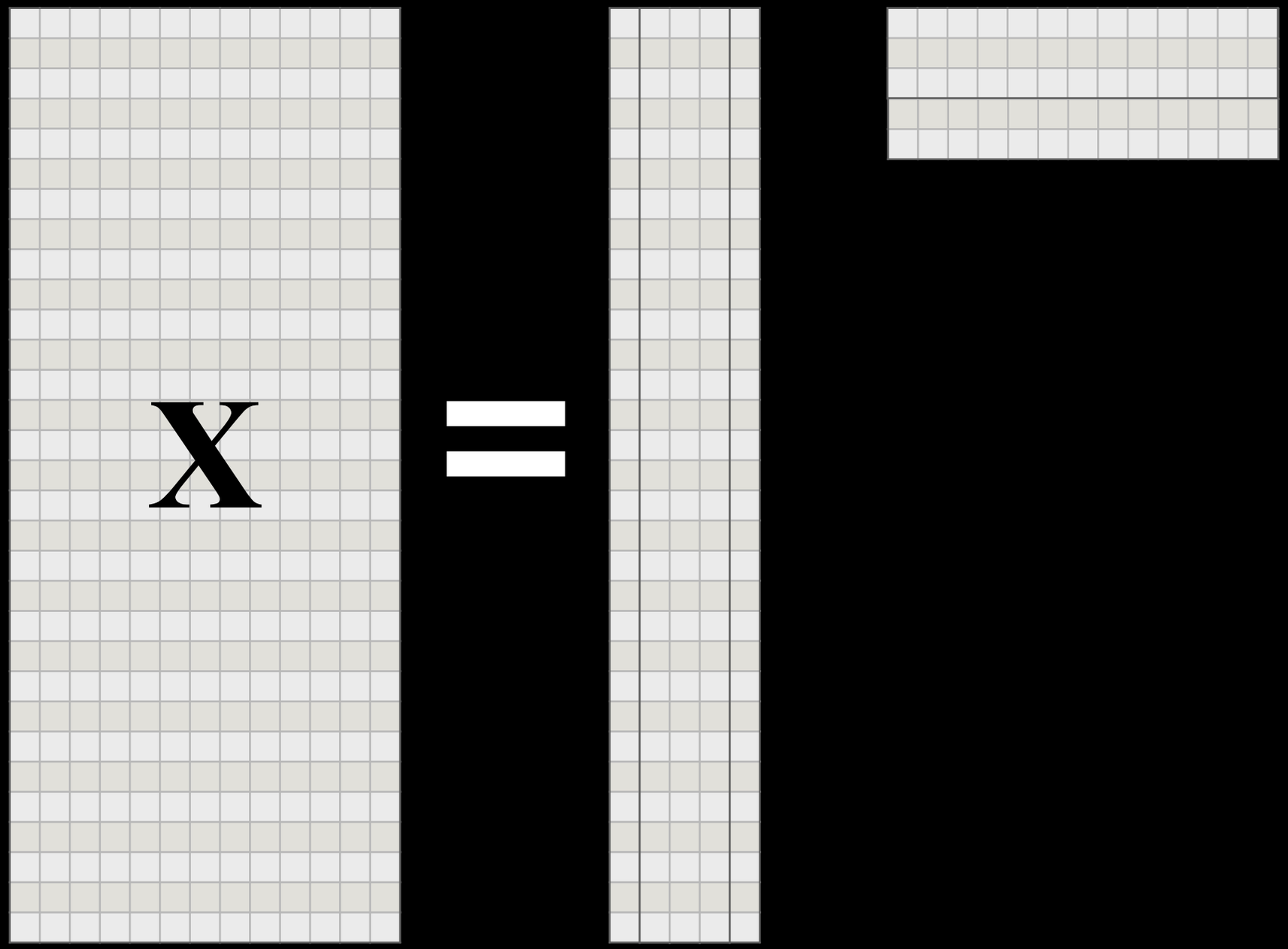


Bocconi

Latent Dimensions

LOWER-DIMENSIONAL

DATA MATRIX DOCUMENT VIEW "TOPICS"

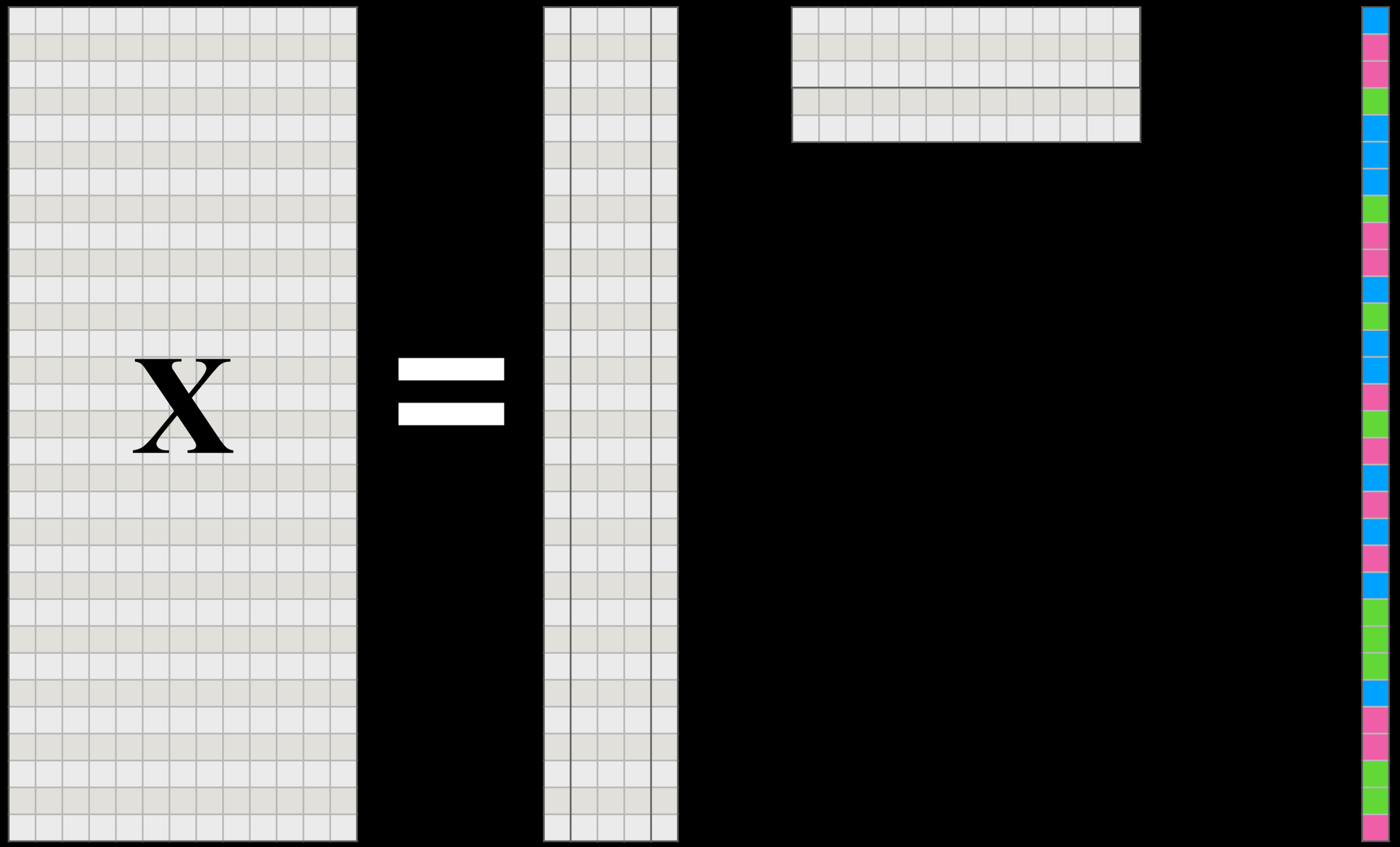


Bocconi

Latent Dimensions

Lower-dimensional

Data Matrix | Document View | "Topics" | Clusters



Bocconi

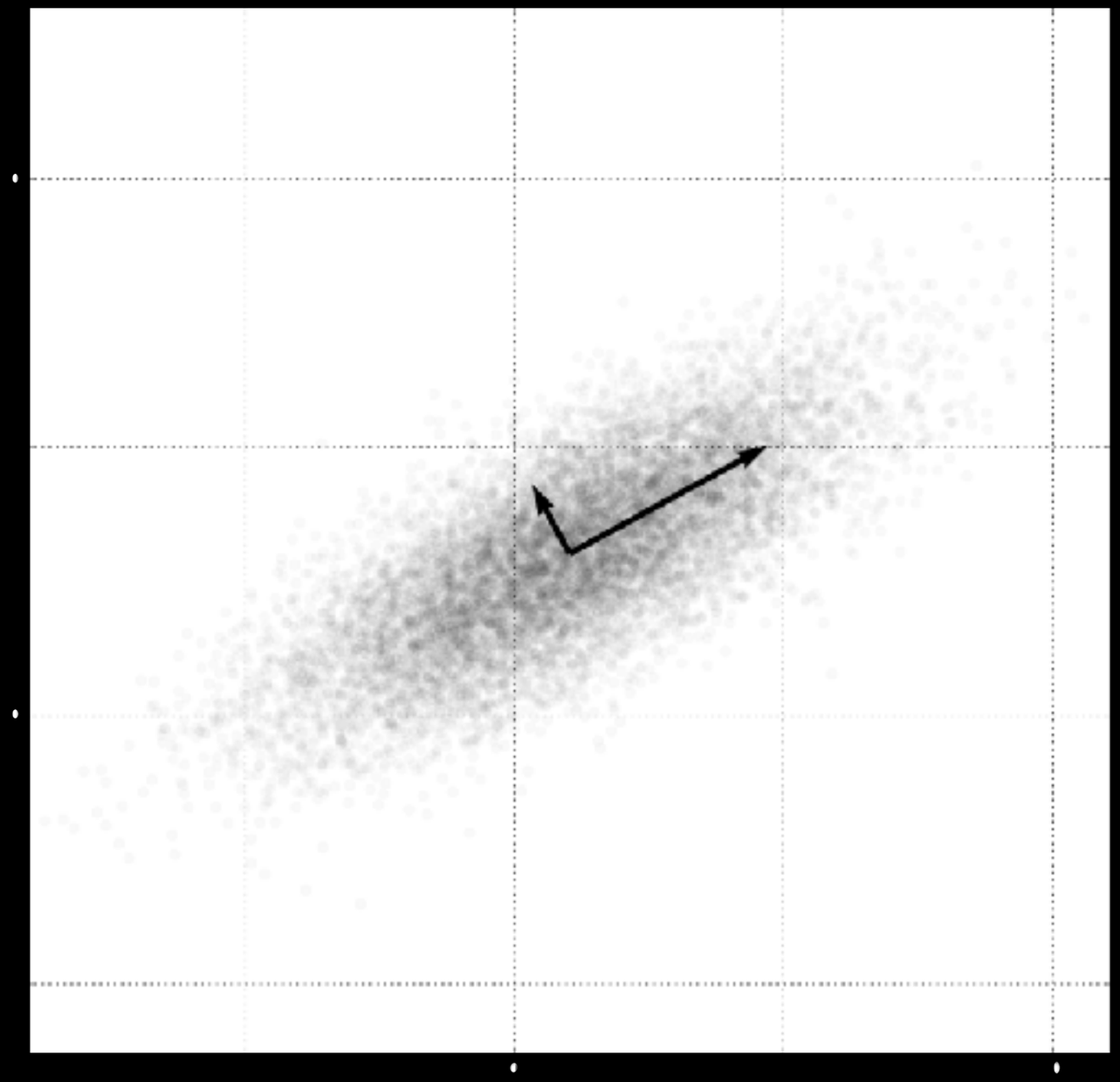
Goals for Today

- Learn about **matrix factorization** and its use for **semantic similarity** and **visualization**
- Learn about ***k*-means** and **agglomerative clustering**
- Learn about **evaluation** criteria

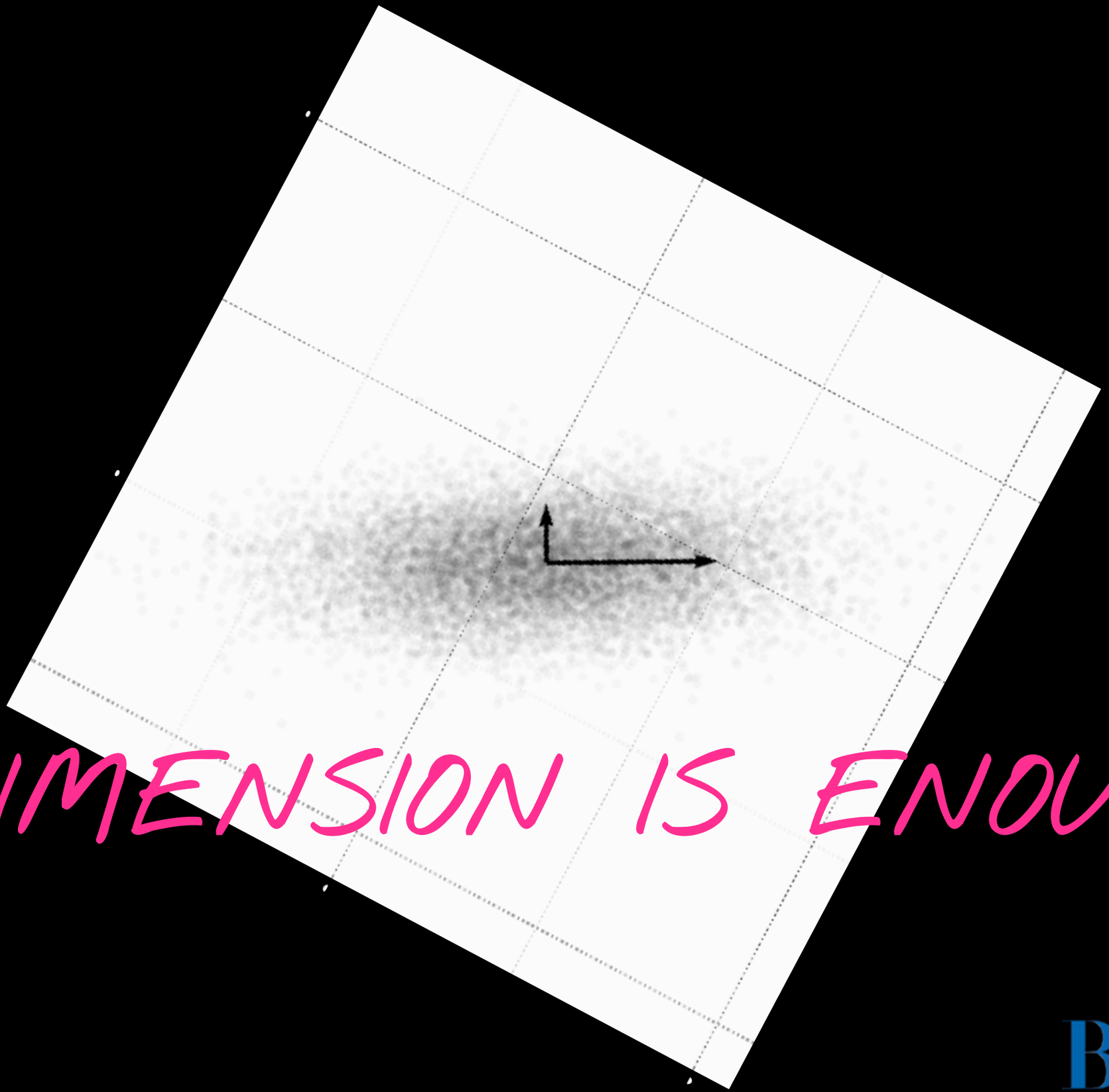
Matrix Factorization

Bocconi

Singular Value Decomposition



Singular Value Decomposition



I DIMENSION IS ENOUGH!

Singular Value Decomposition

- “principal component analysis”: discover the dimensions that matter
- idea: matrix is made up of few hidden dimensions
- Dimensions correspond to **documents**, **terms**, and latent **concepts**

Singular Value Decomposition

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M TERMS

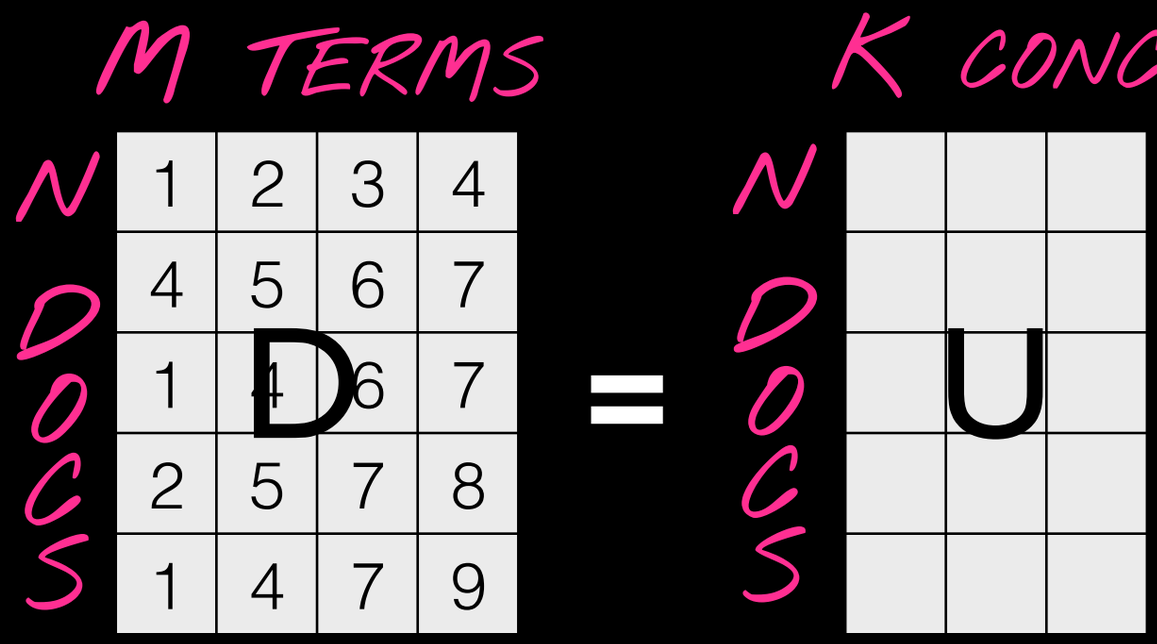
N DOCS

1	2	3	4
4	5	6	7
1	4	6	7
2	5	7	8
1	4	7	9

D =

Singular Value Decomposition

- “principal component analysis”: discover the dimensions that matter
- idea: matrix is made up of few hidden dimensions
- Dimensions correspond to **documents**, **terms**, and latent **concepts**



Bocconi

Singular Value Decomposition

- “principal component analysis”: discover the dimensions that matter
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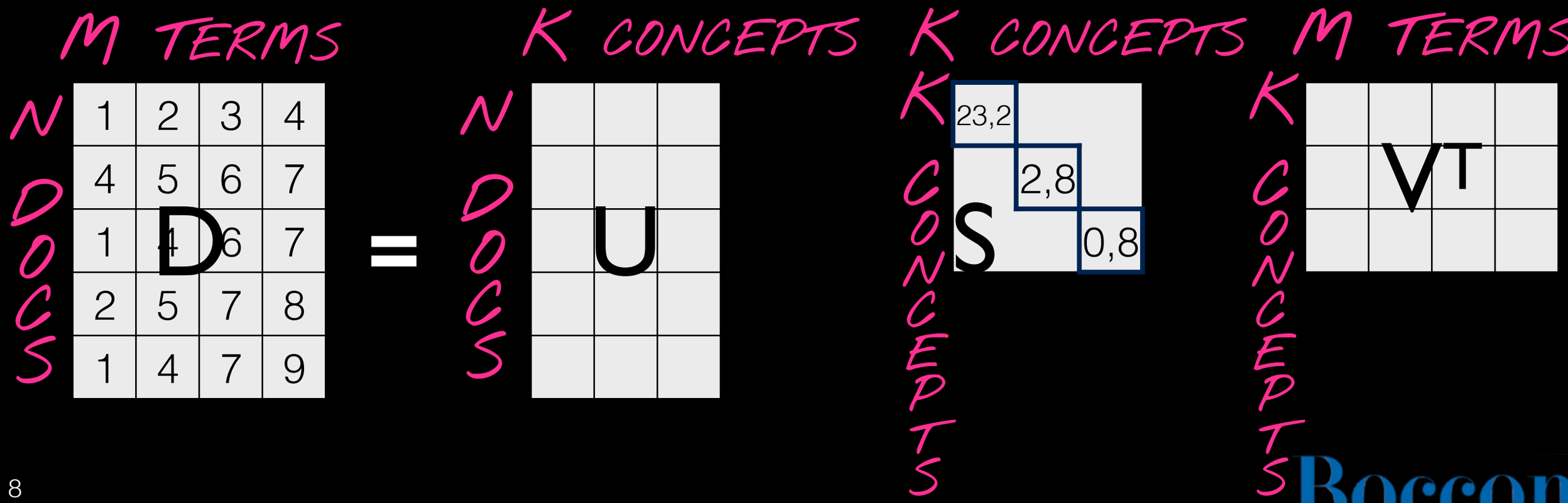
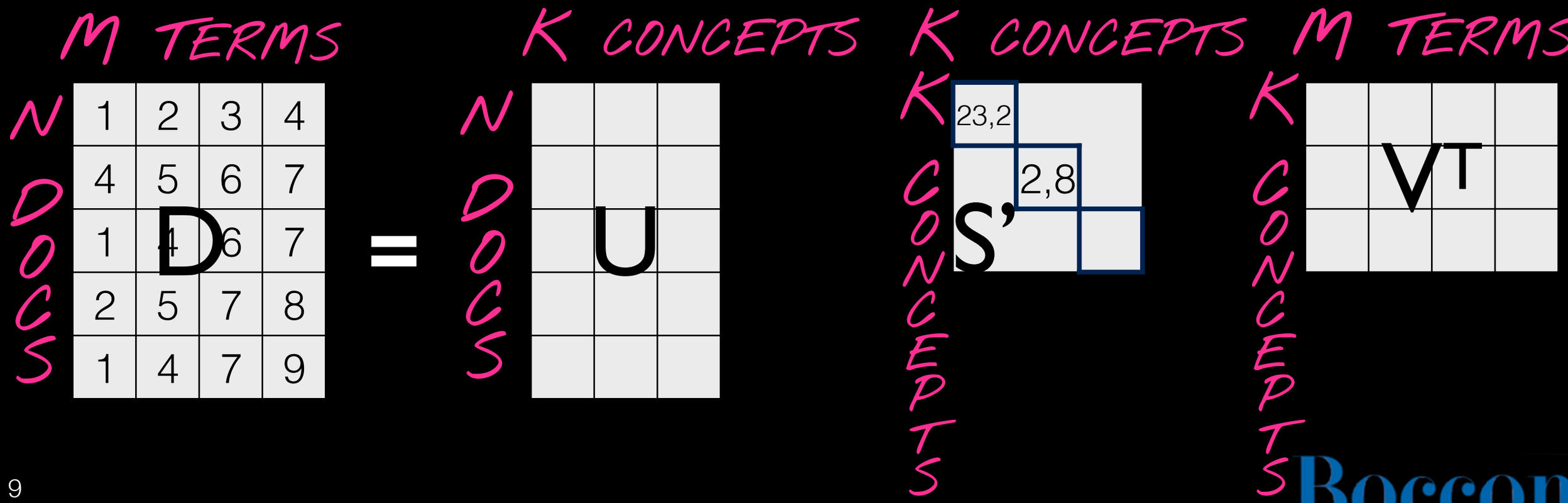


Bocconi

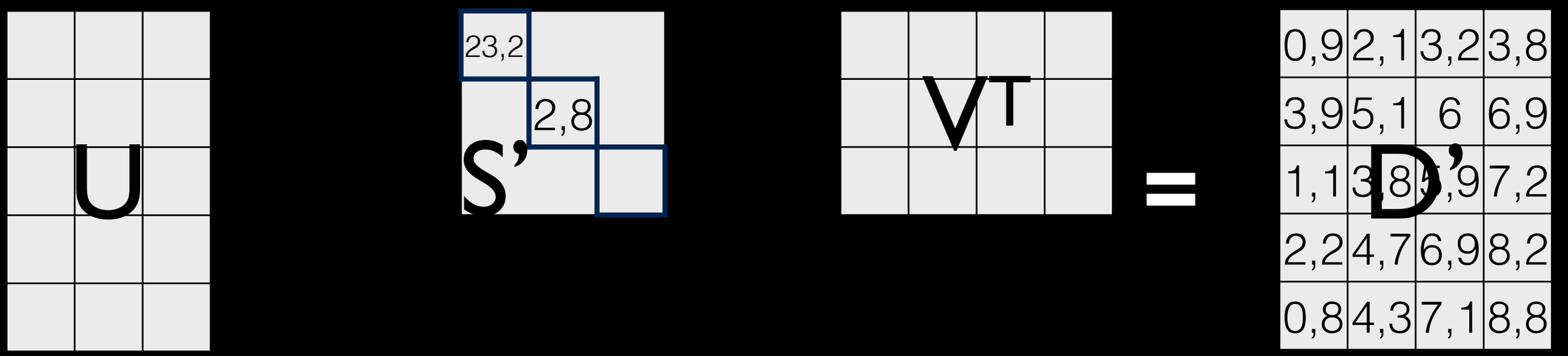
Singular Value Decomposition

- reduce principal components/concepts to smaller number



Singular Value Decomposition

- reconstruct original matrix in new concept space:
  Latent Semantic Analysis



Singular Value Decomposition

- reconstruct original matrix in new concept space:
  Latent Semantic Analysis

1	2	3	4
4	5	6	7
1	4	6	7
2	5	7	8
1	4	7	9

D

0,9	2,1	3,2	3,8
3,9	5,1	6	6,9
1,1	3,8	5,9	7,2
2,2	4,7	6,9	8,2
0,8	4,3	7,1	8,8

D’

Non-negative Matrix Factorization

- Use only positive values
- Find approximation of two components

M TERMS

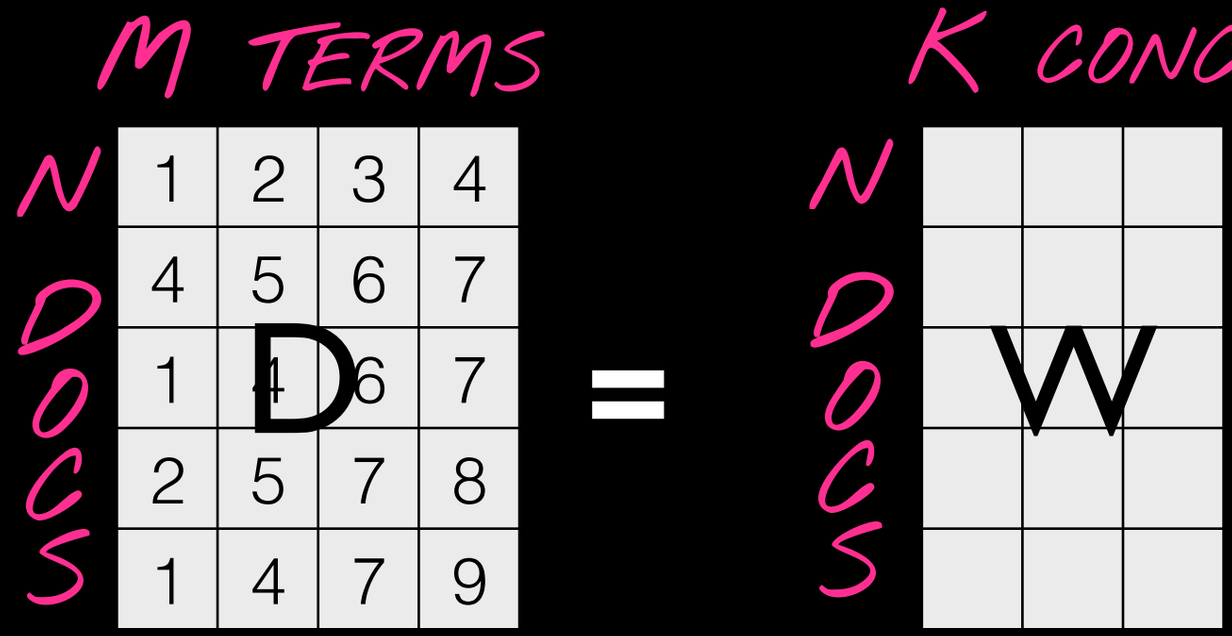
N DOCS

1	2	3	4
4	5	6	7
1	4	6	7
2	5	7	8
1	4	7	9

D =

Non-negative Matrix Factorization

- Use only positive values
- Find approximation of two components



Bocconi

Non-negative Matrix Factorization

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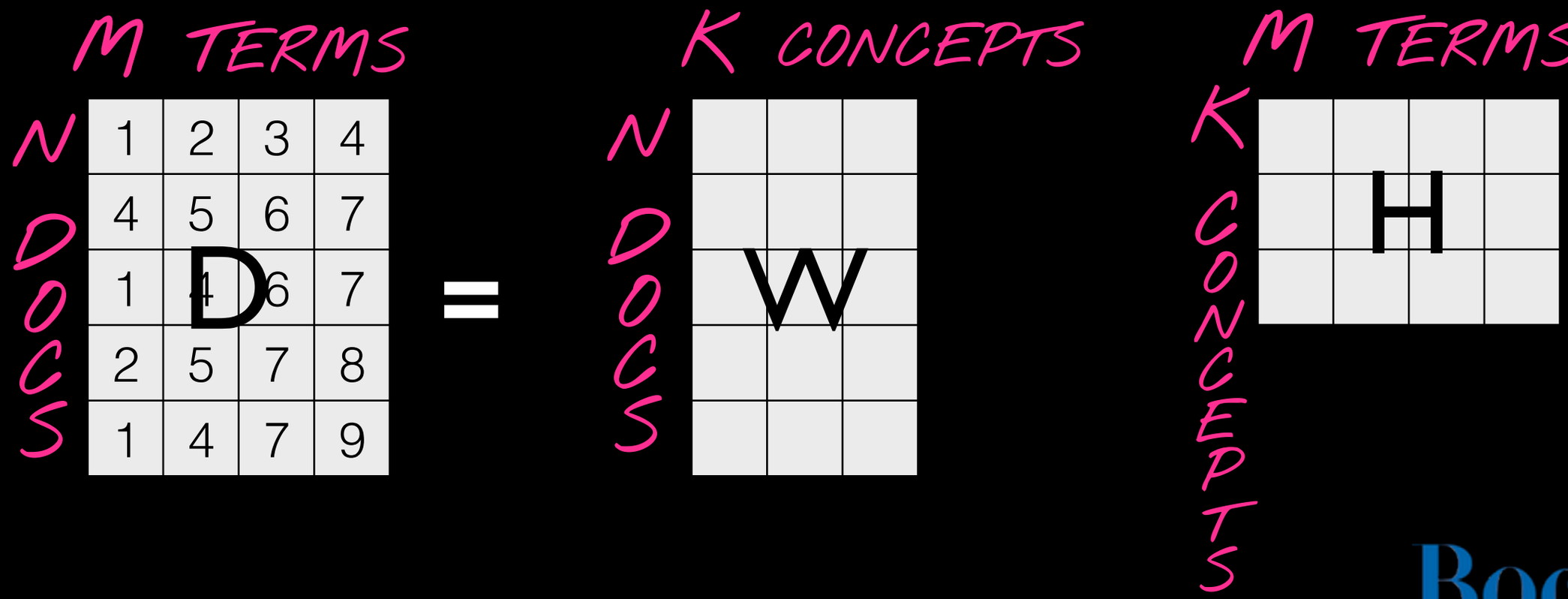

Bocconi

Non-negative Matrix Factorization

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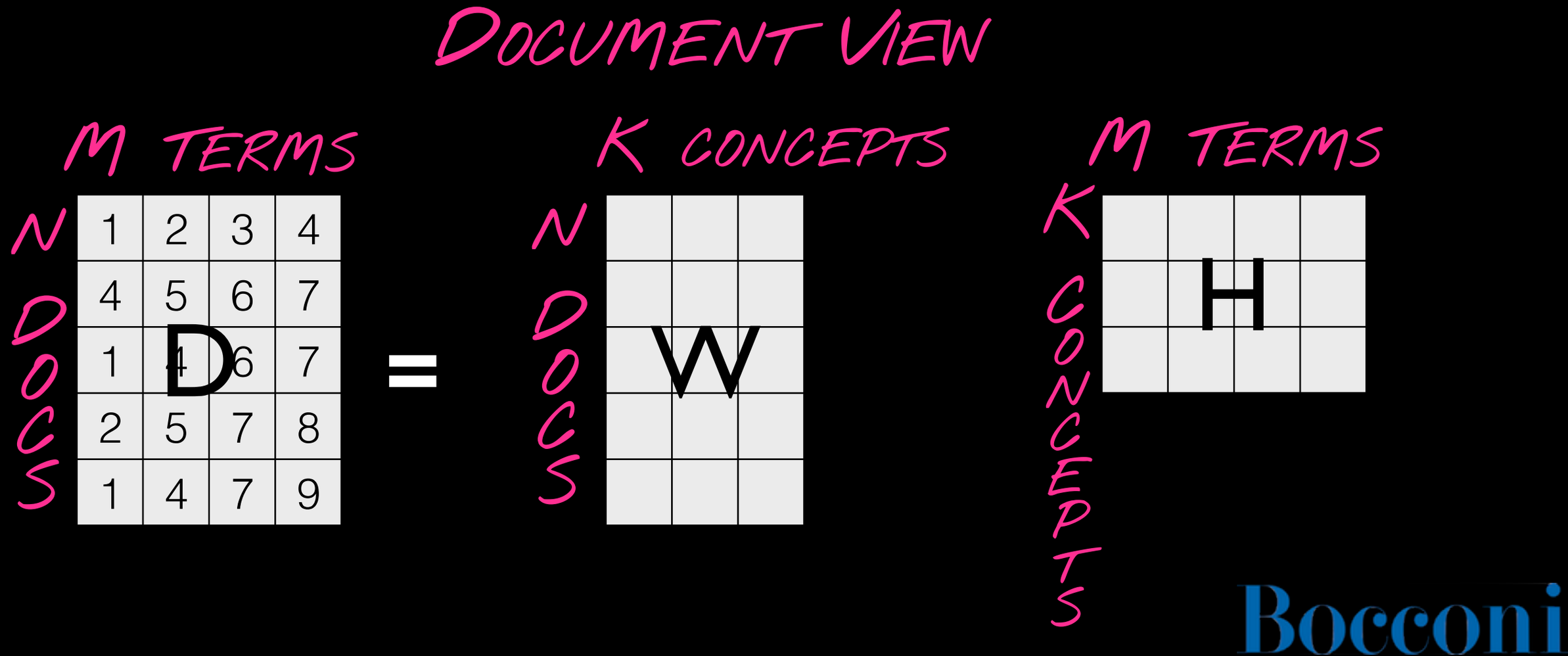

Bocconi

Non-negative Matrix Factorization

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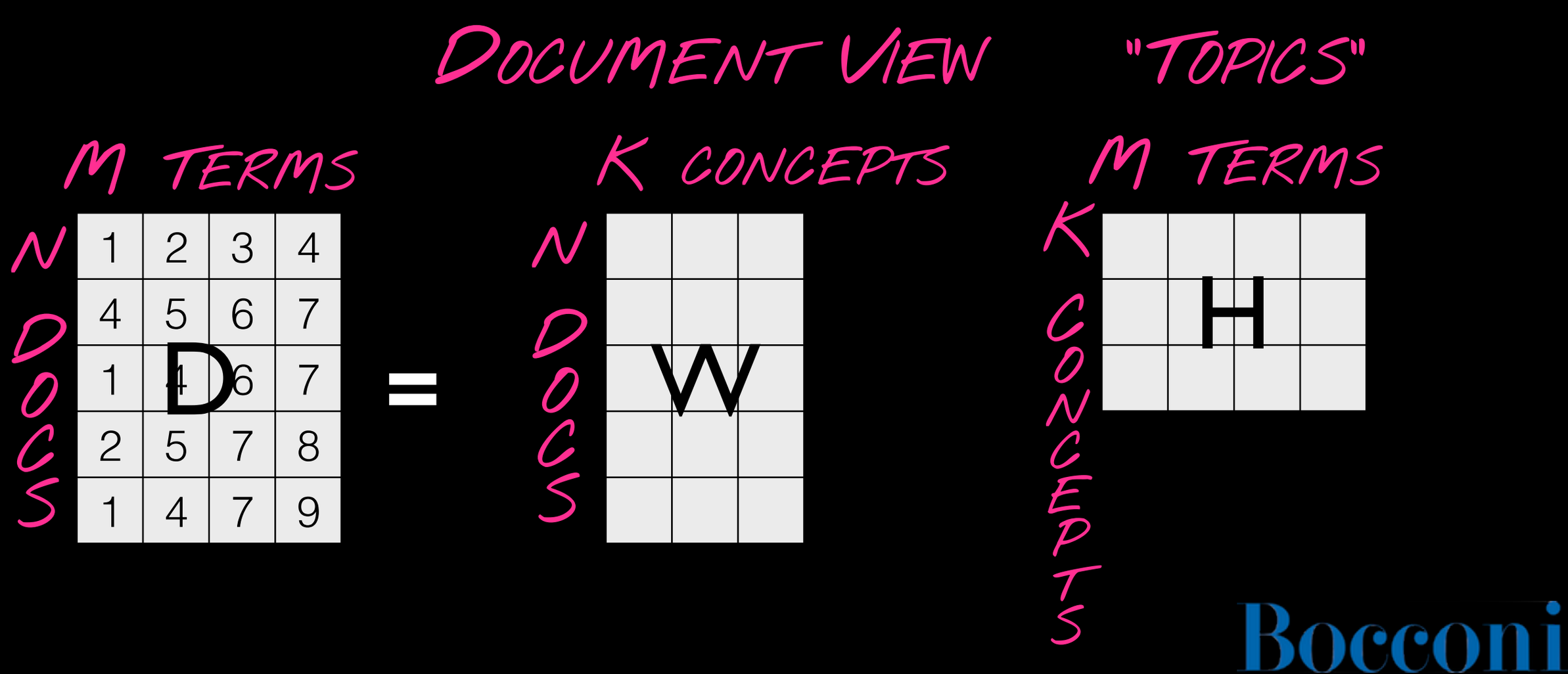


Bocconi

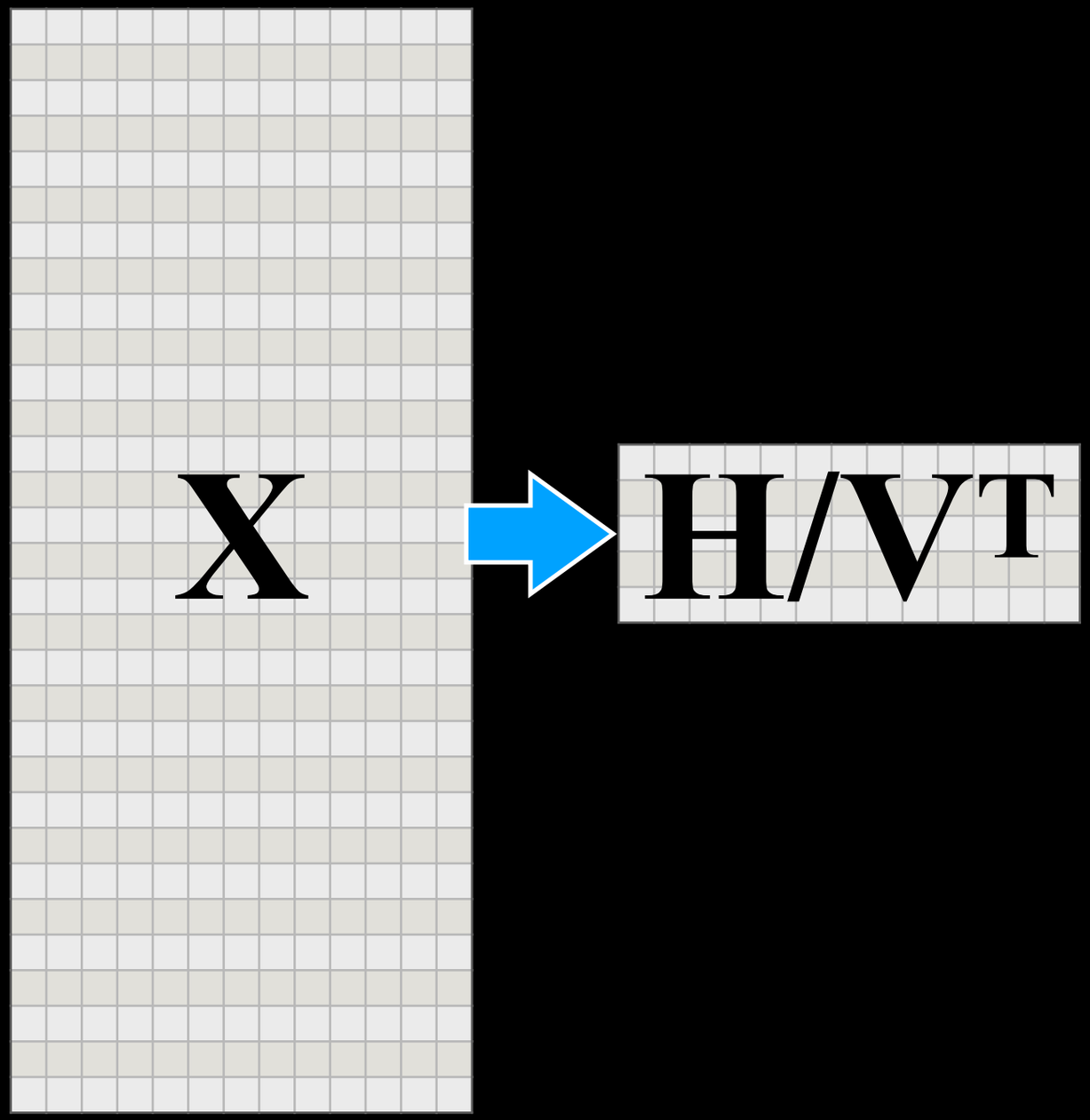
Comparison

	SVD	NMF
Negative values (embeddings) as input?	yes	no
#components	3: U, S, V	2: W, H
document view?	yes: U	yes: W
term view?	yes: V	yes: H
strength ranking?	yes: S	no
exact?	yes	no
"topic" quality	mixed	better
sparsity	low	medium

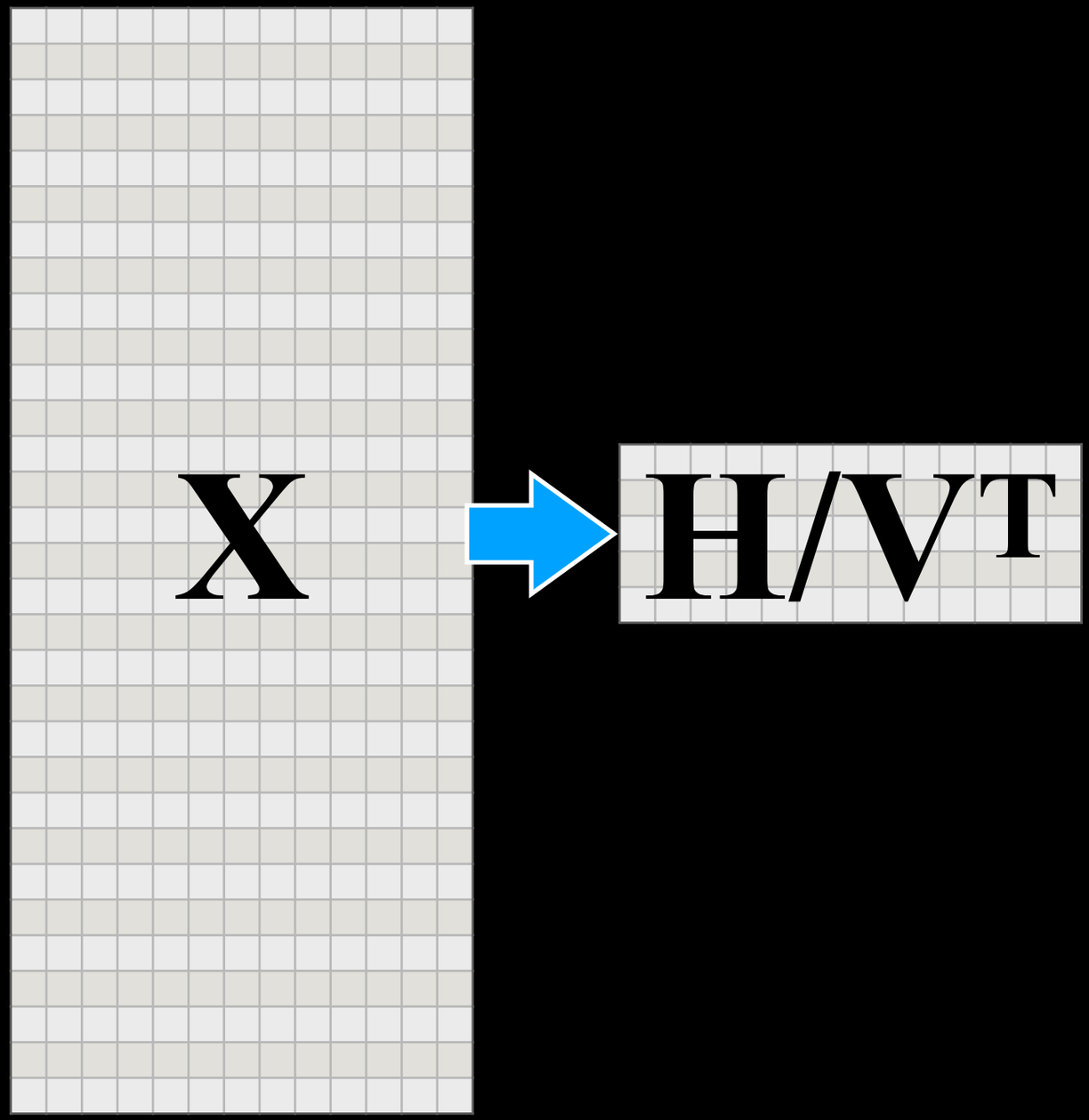
Yes, but: What is it Good for?

- Find latent **topic** dimensions (alternative: LDA)
- Find **word similarity** in latent space (alternative: Word2Vec)
- Find **document similarity** in latent space (alternative: Doc2Vec)
- Reduce dimensionality for **visualization**

Latent Word Dimension Topics

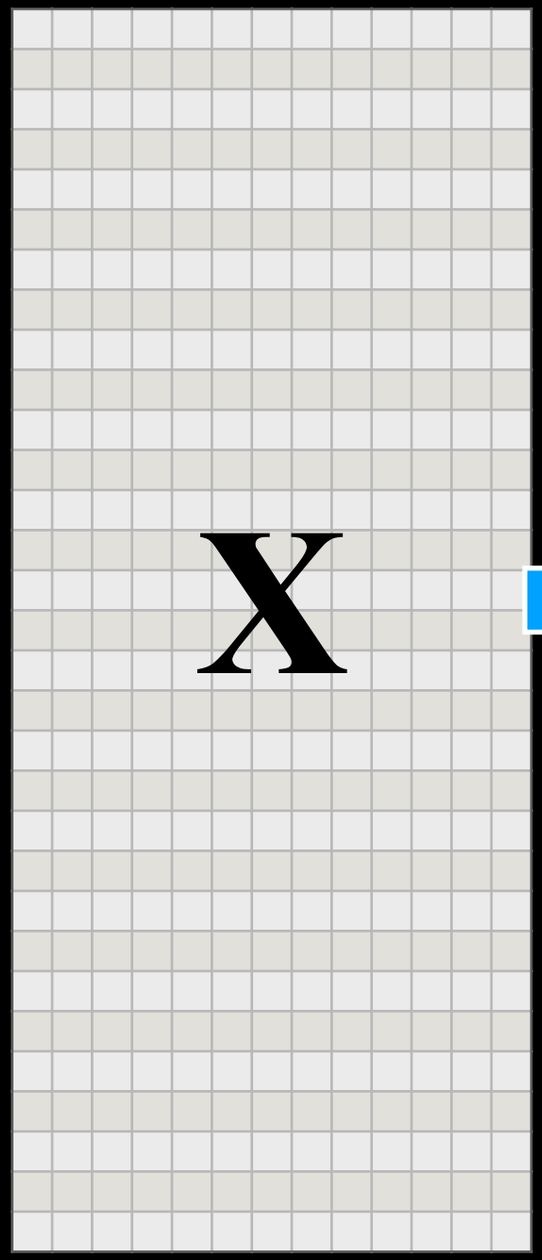


Latent Word Dimension Topics



NMF(10)
FOR MOBY DICK

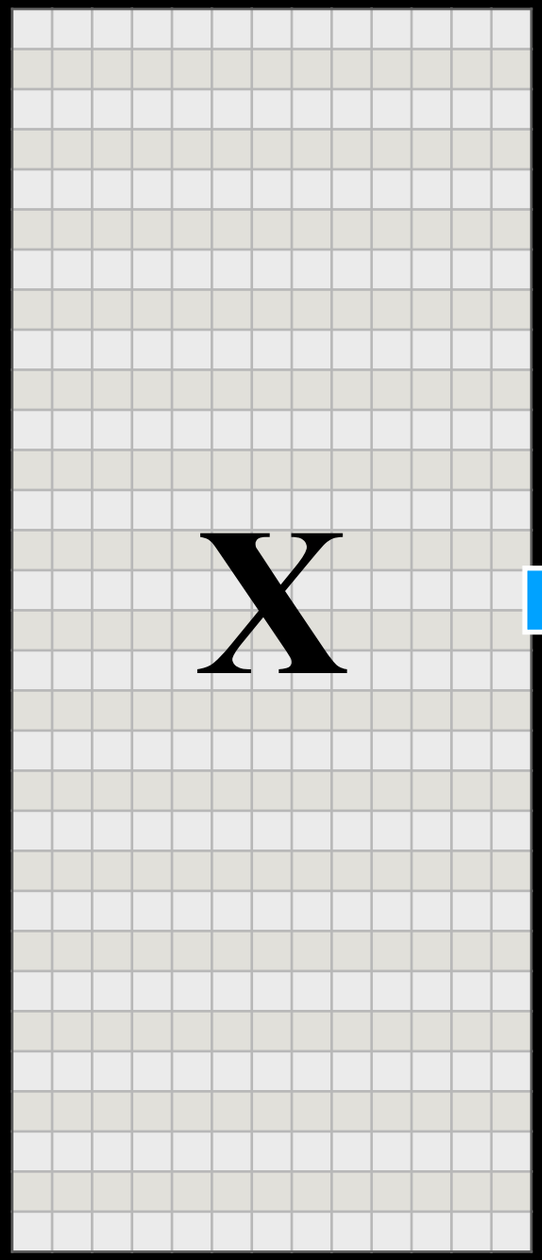
Latent Word Dimension Topics



NMF(10) FOR MOBY DICK

ahab, captain, cried, captain ahab, cried ahab
chapter, folio, octavo, ii, iii
like, ship, sea, time, way
man, old, old man, look, young man
oh, life, starbuck, sweet, god
said, stubb, queequeg, don, starbuck
sir, aye, let, shall, think
thou, thee, thy, st, god
whale, sperm, sperm whale, white, white whale
ye, look, say, ye ye, men

Latent Word Dimension Topics



NMF(10) FOR MOBY DICK

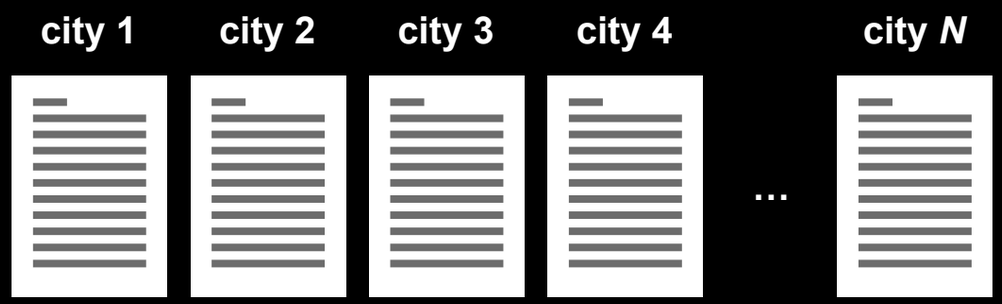
AHAB	ahab, captain, cried, captain ahab, cried ahab
STRUCTURE	chapter, folio, octavo, ii, iii
???	like, ship, sea, time, way
MEN	man, old, old man, look, young man
???	oh, life, starbuck, sweet, god
CHARACTERS	said, stubb, queequeg, don, starbuck
???	sir, aye, let, shall, think
OLD-TIMEY	thou, thee, thy, st, god
WHALES	whale, sperm, sperm whale, white, white whale
???	ye, look, say, ye ye, men

Dimensionality Reduction for Visualizations

Bocconi

Hovy & Purschke, 2018

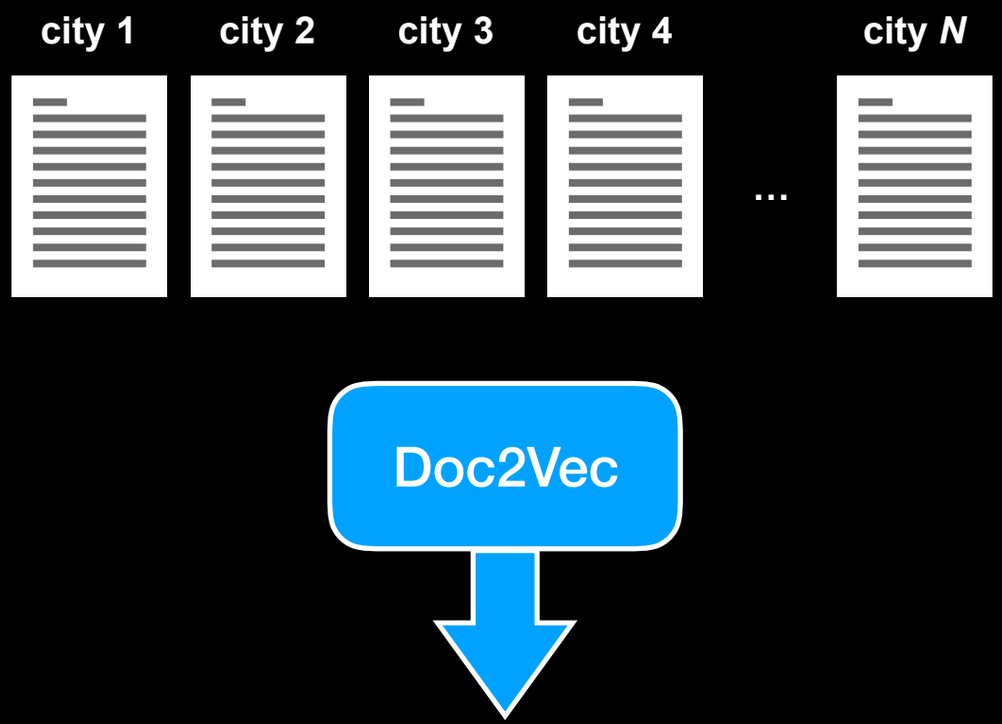
Dimensions as RGB



Bocconi

Hovy & Purschke, 2018

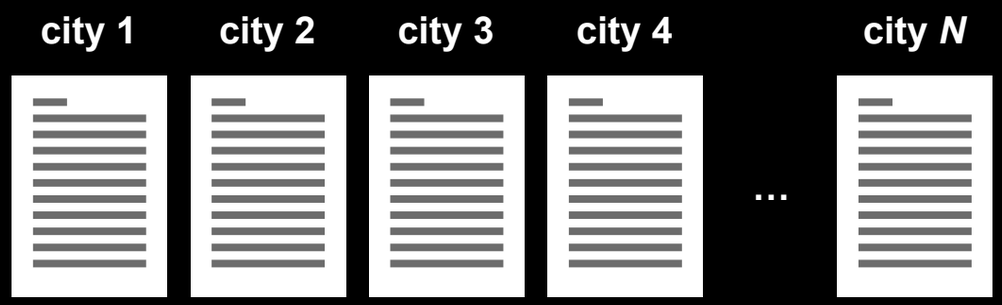
Dimensions as RGB

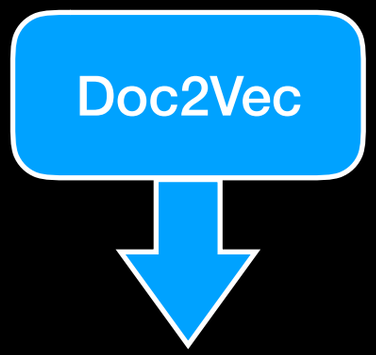


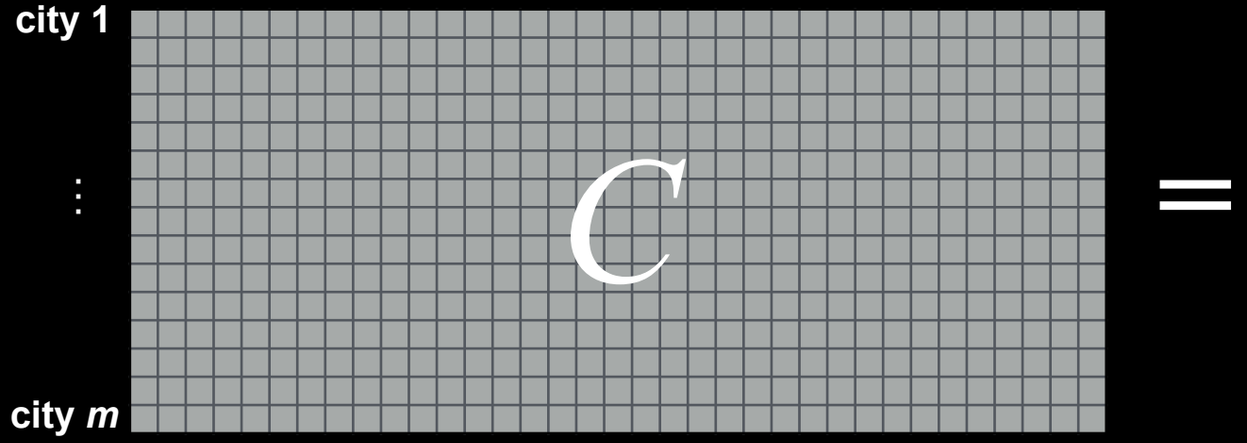
Bocconi

Hovy & Purschke, 2018

Dimensions as RGB





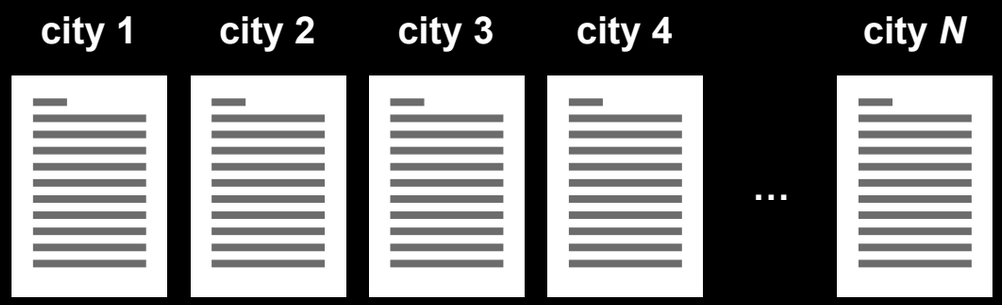


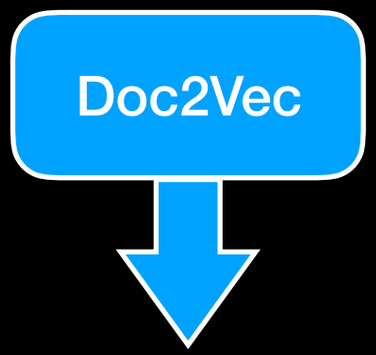
Dense Representation

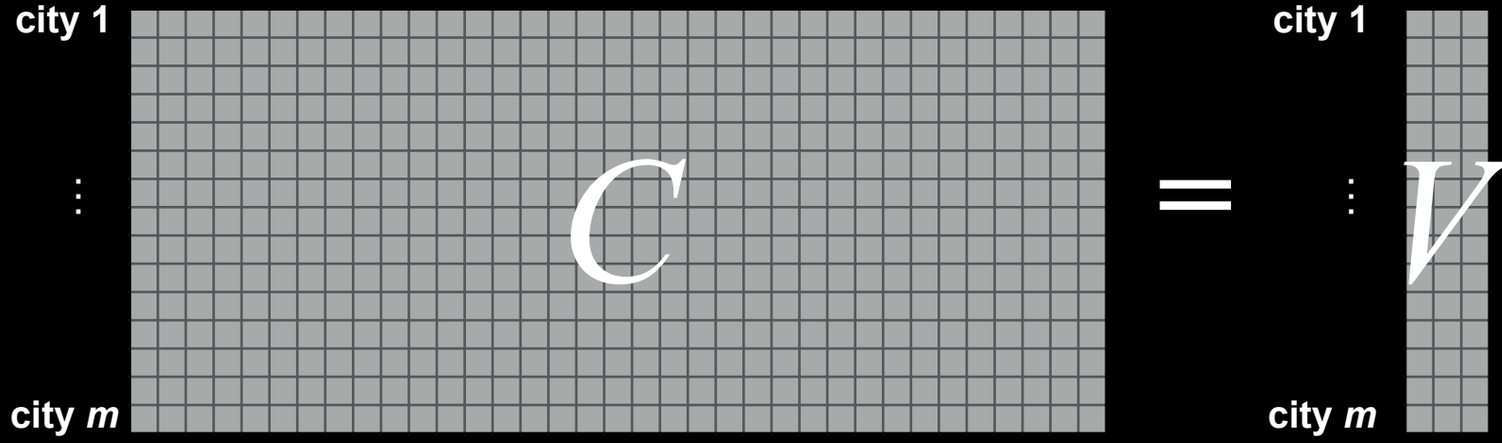
Bocconi

Hovy & Purschke, 2018

Dimensions as RGB







Dense Representation

Bocconi

Hovy & Purschke, 2018

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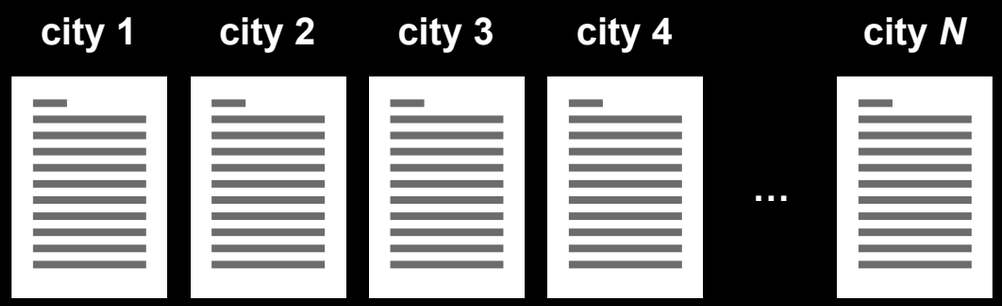
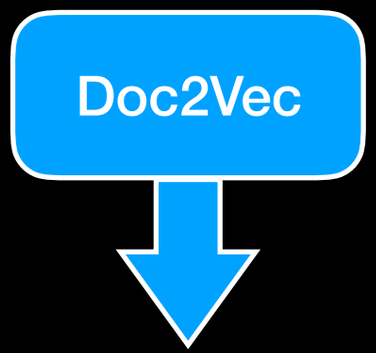
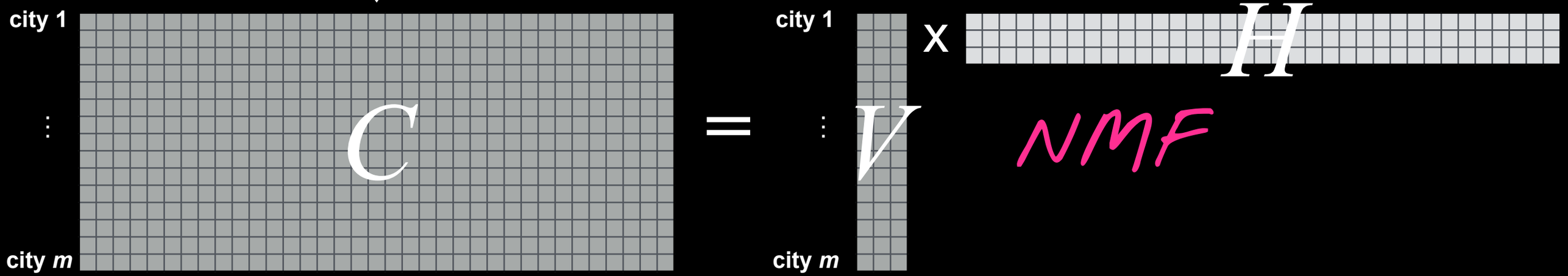






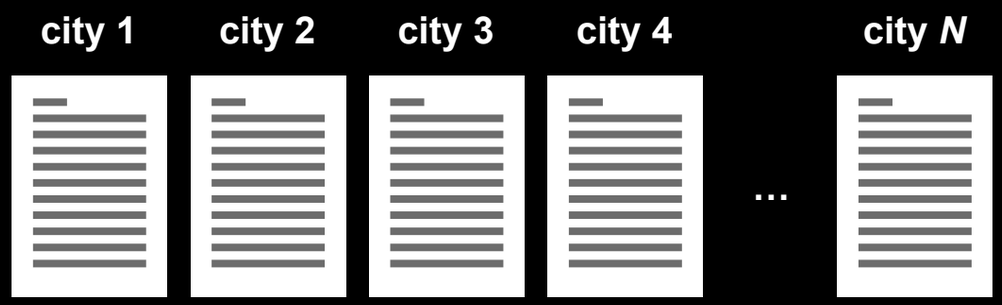
NMF

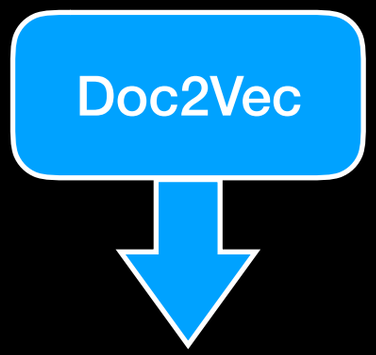
Dense Representation

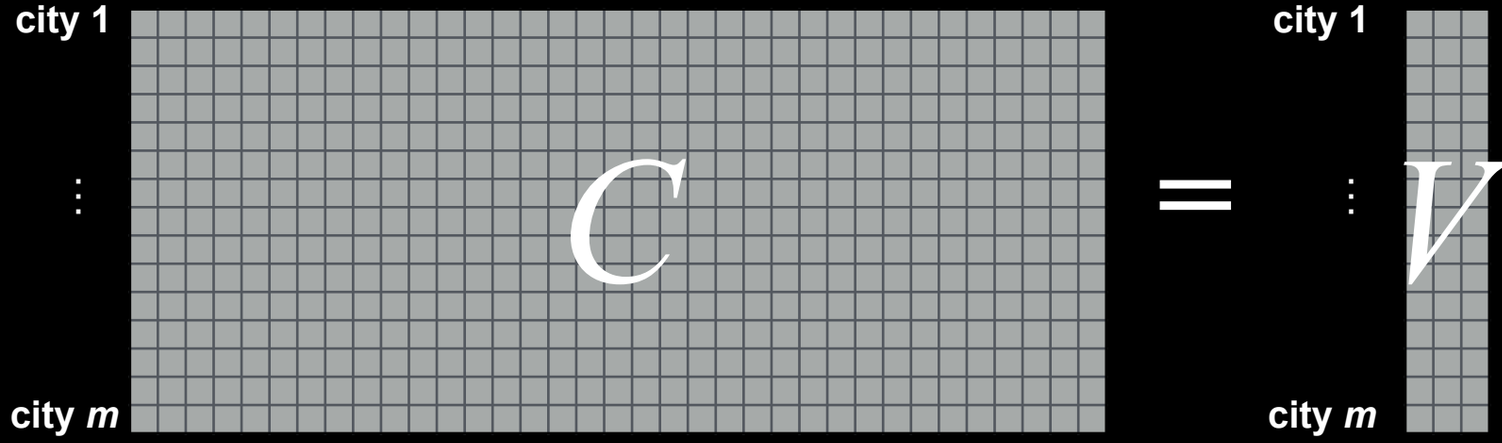
Bocconi

Hovy & Purschke, 2018

Dimensions as RGB



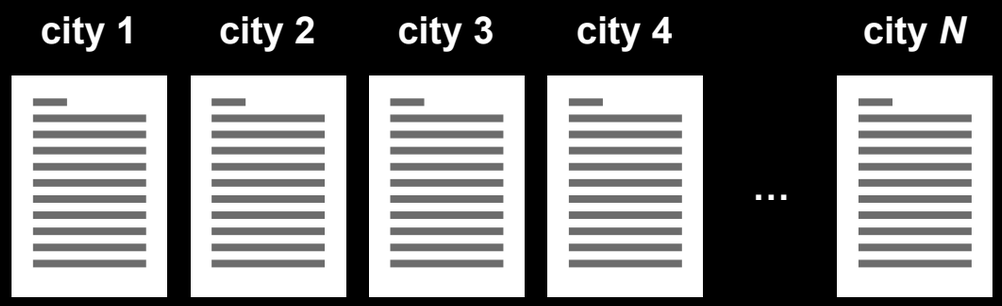




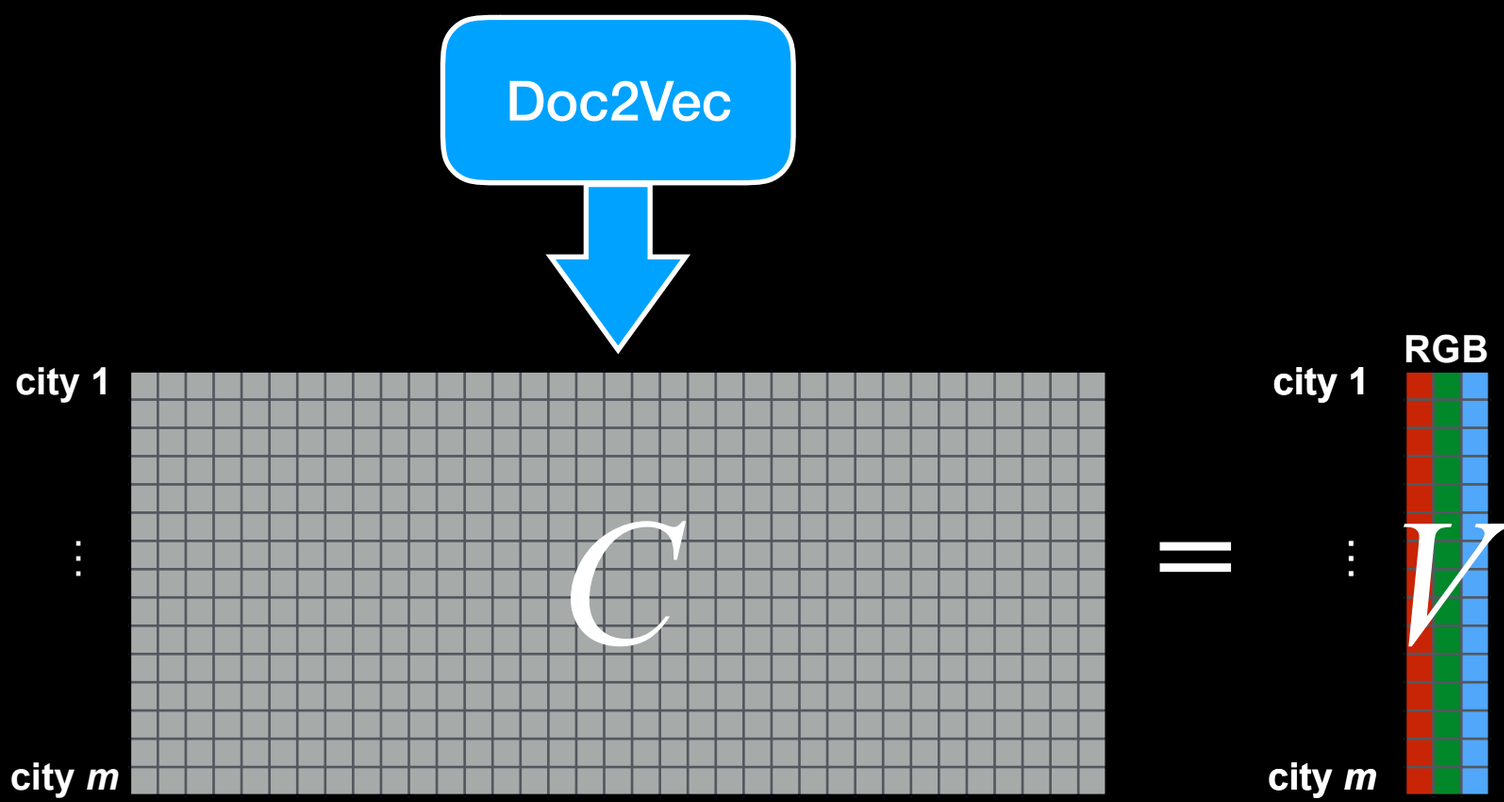
Dense Representation

Bocconi

Dimensions as RGB



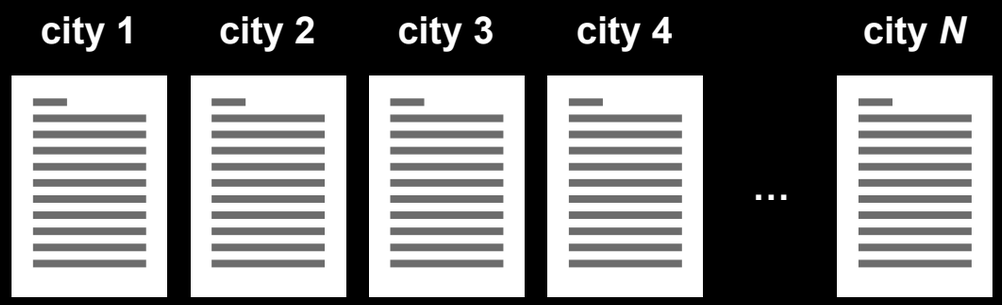
Doc2Vec

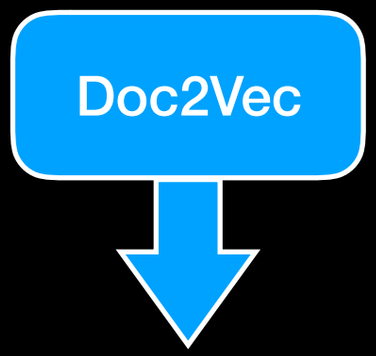


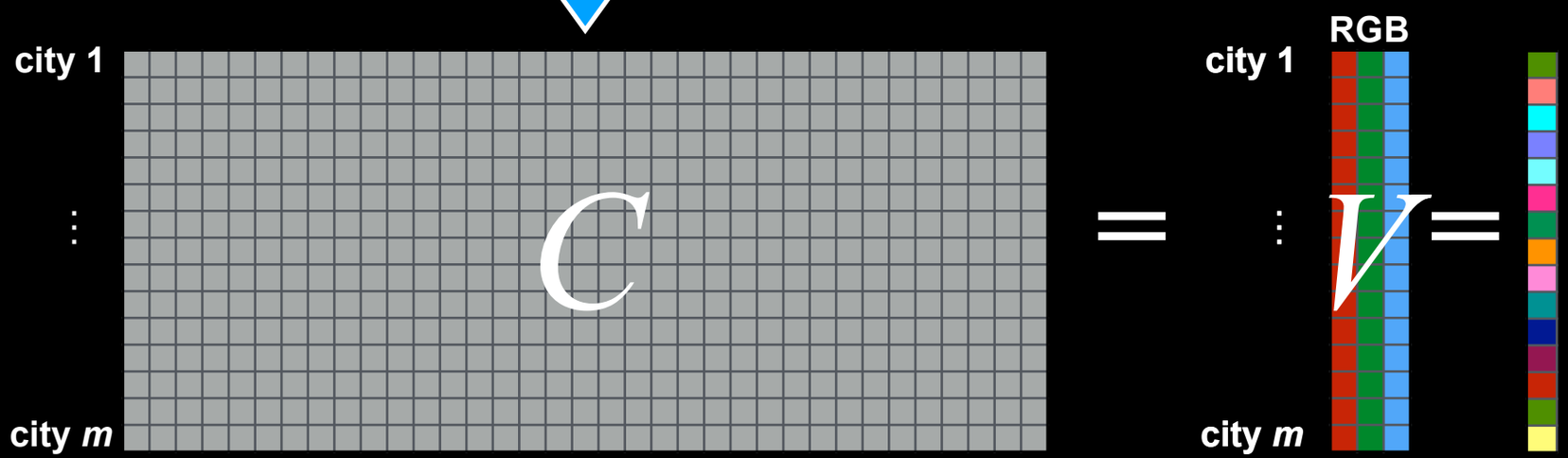
Dense Representation

Hovy & Purschke, 2018

Dimensions as RGB





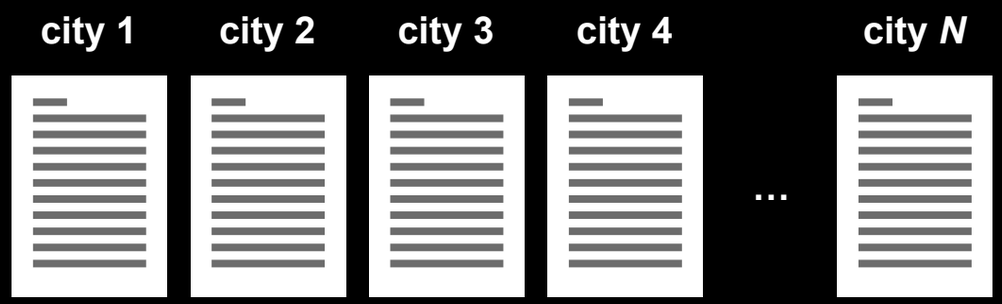


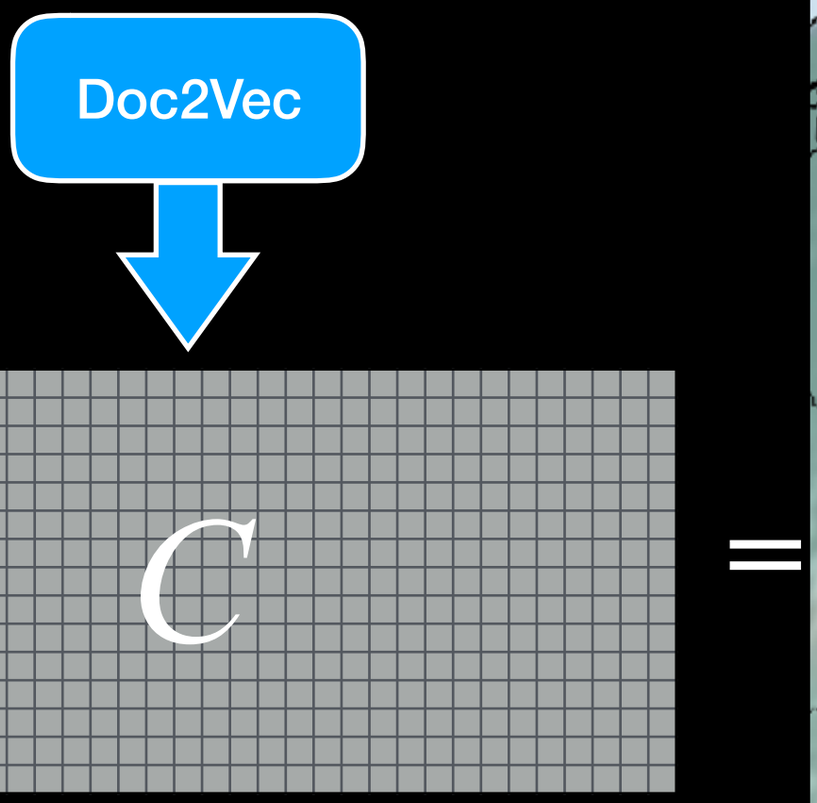
Dense Representation

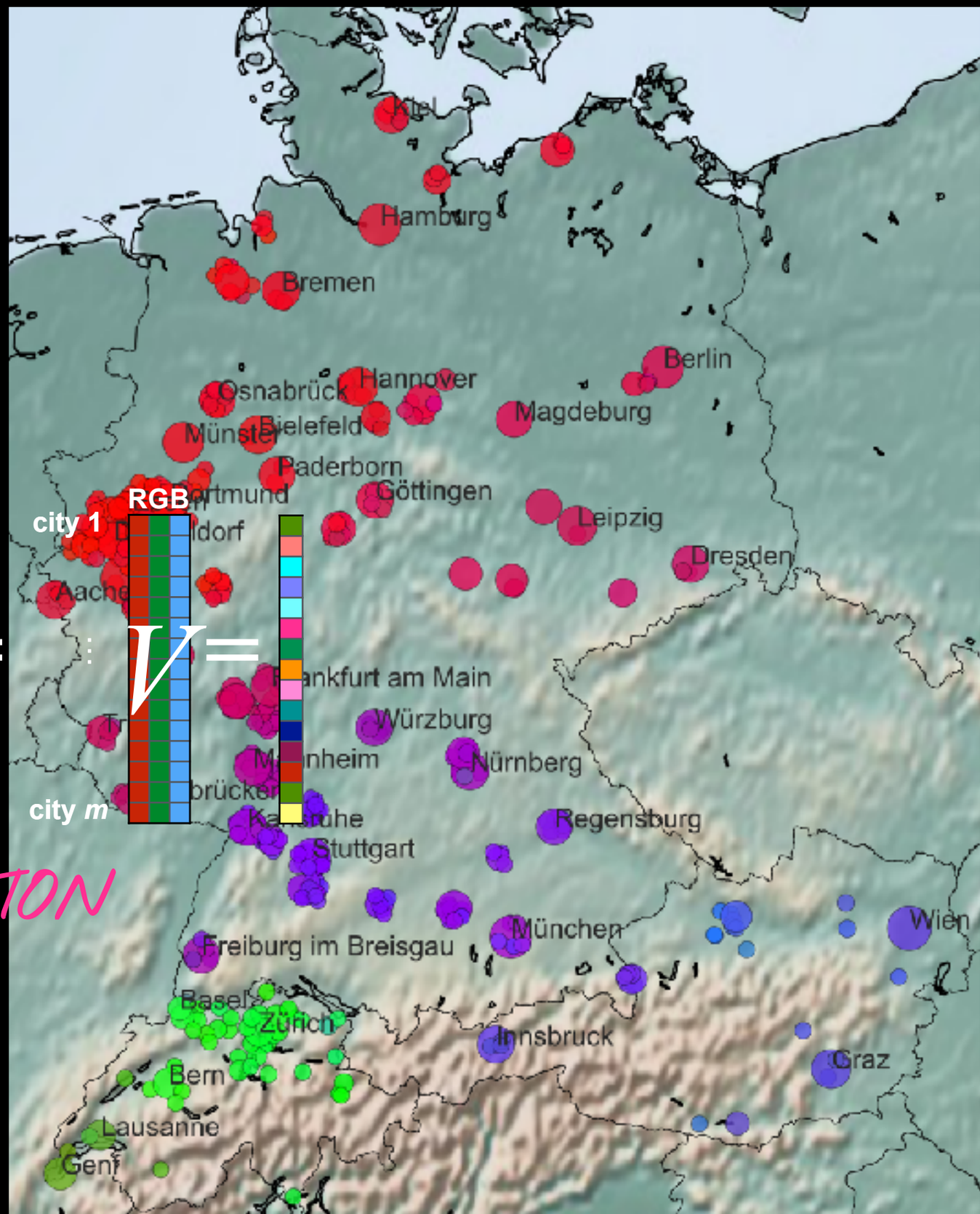
Bocconi

Hovy & Purschke, 2018

Dimensions as RGB



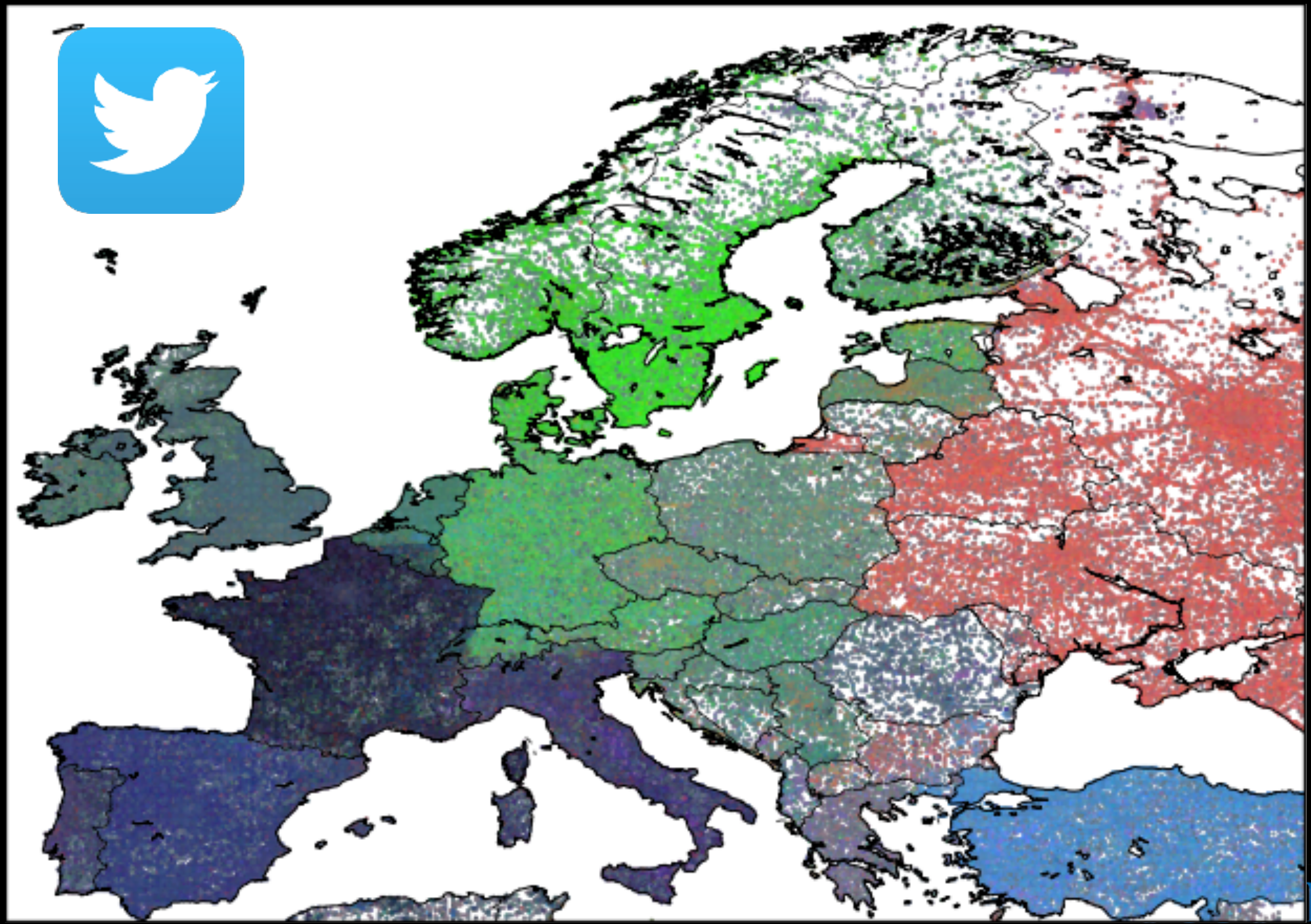




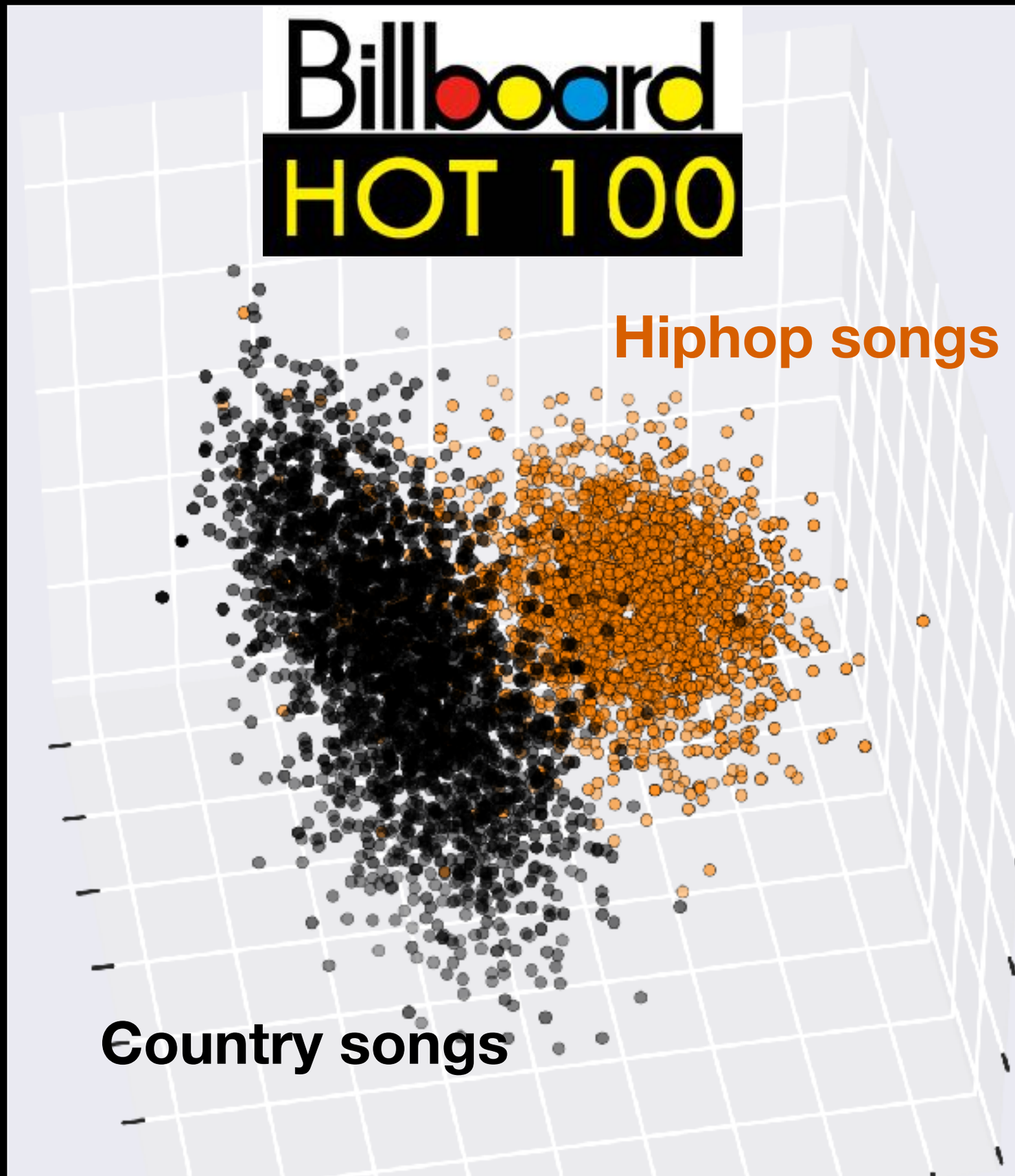
Dense Representation

Hovy et al., 2019

Dimensions as RGB



Dimensions as Coordinates



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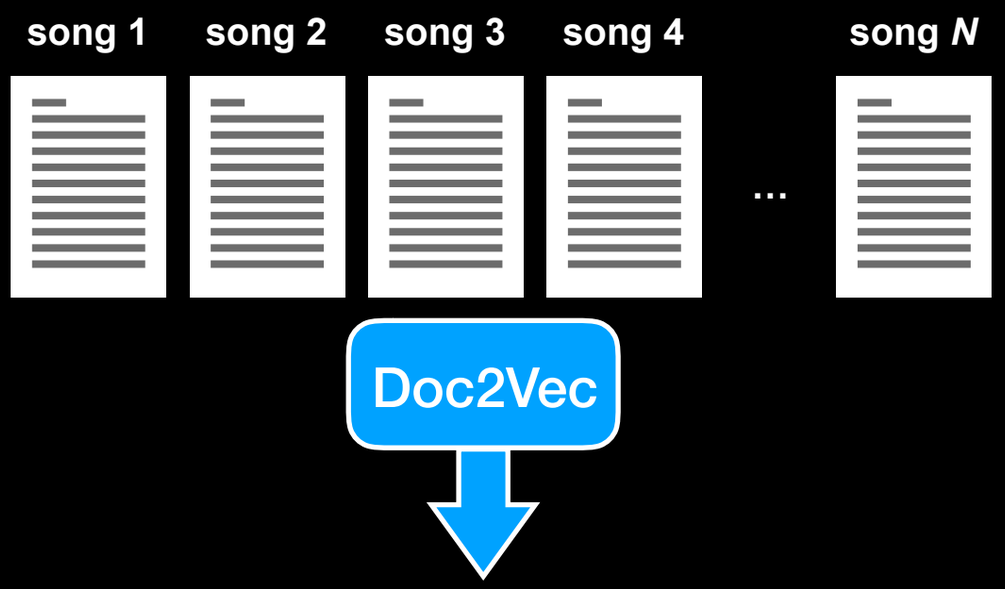

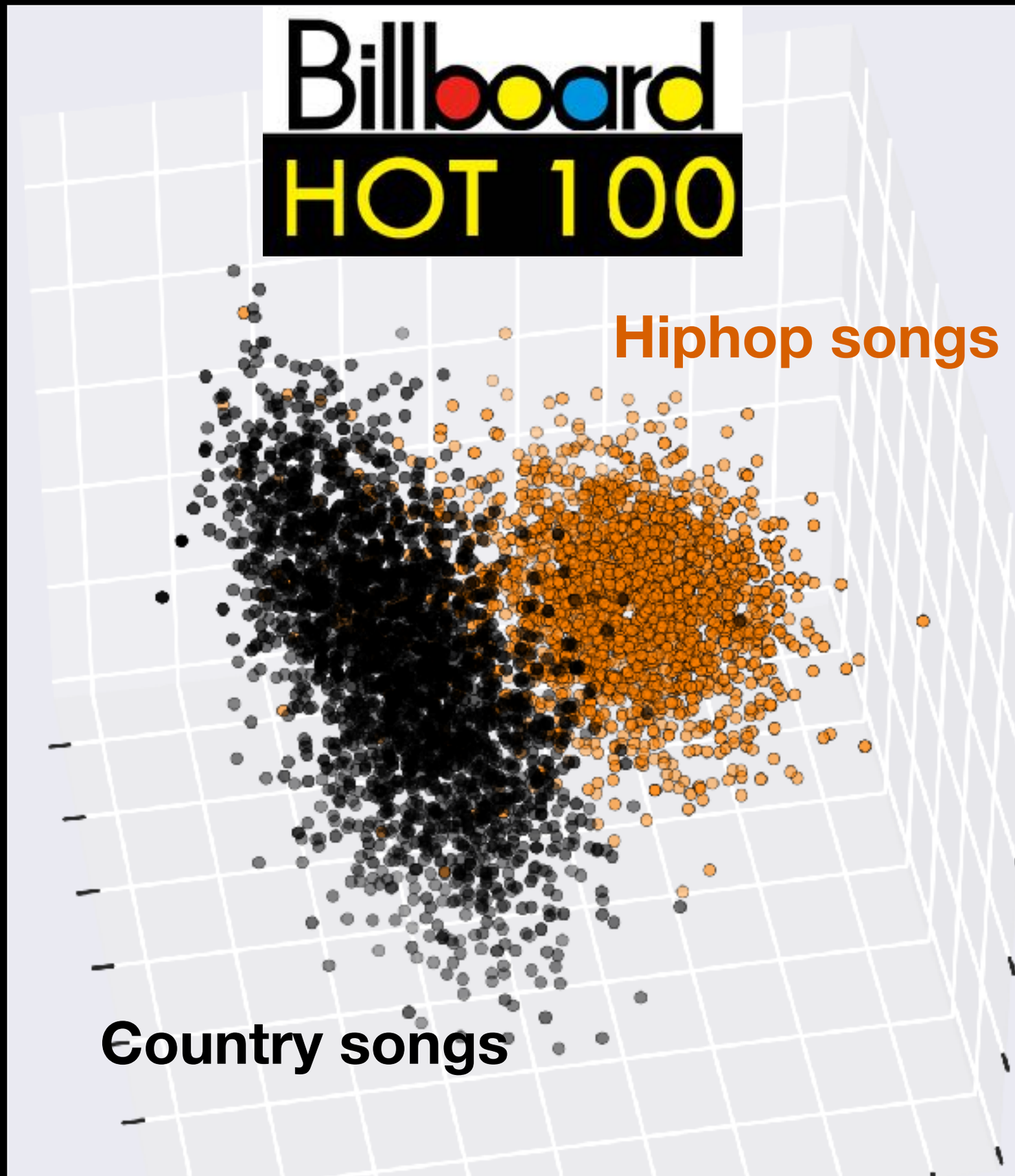

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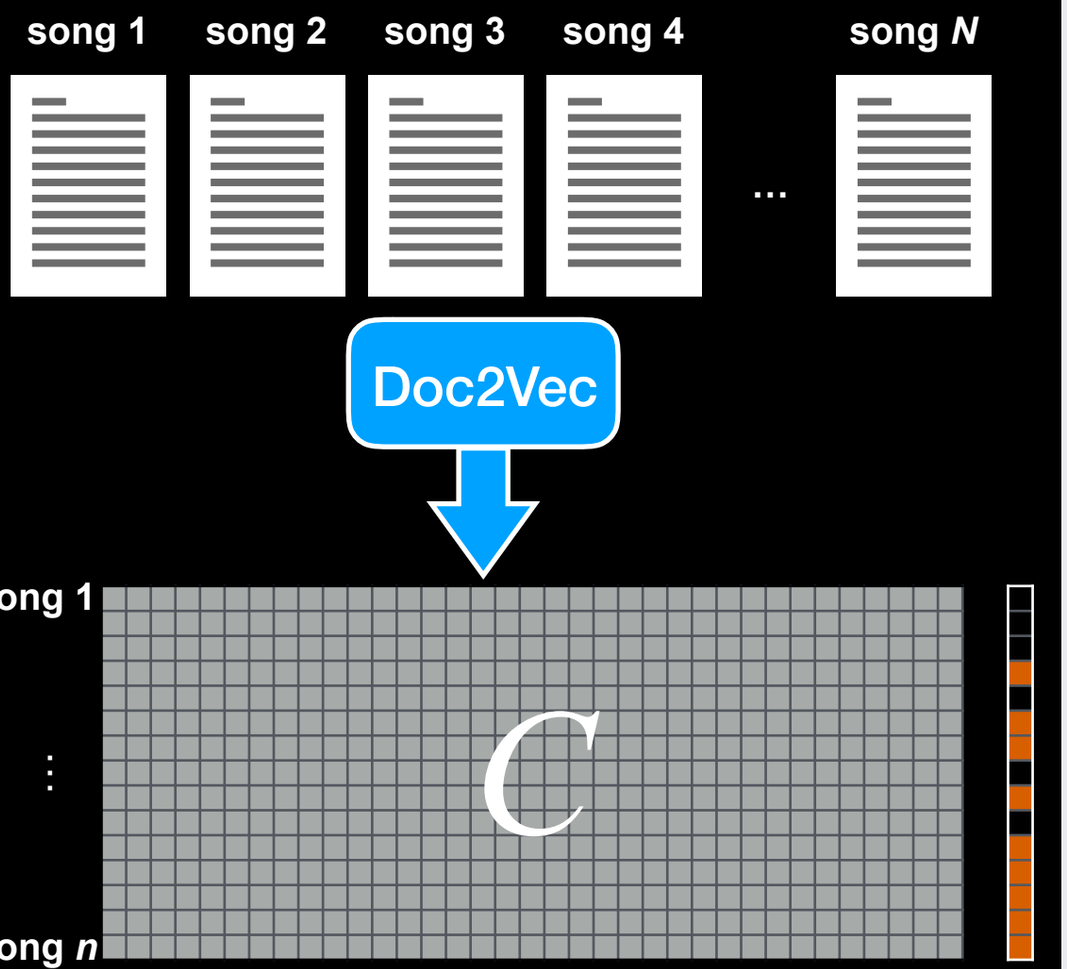
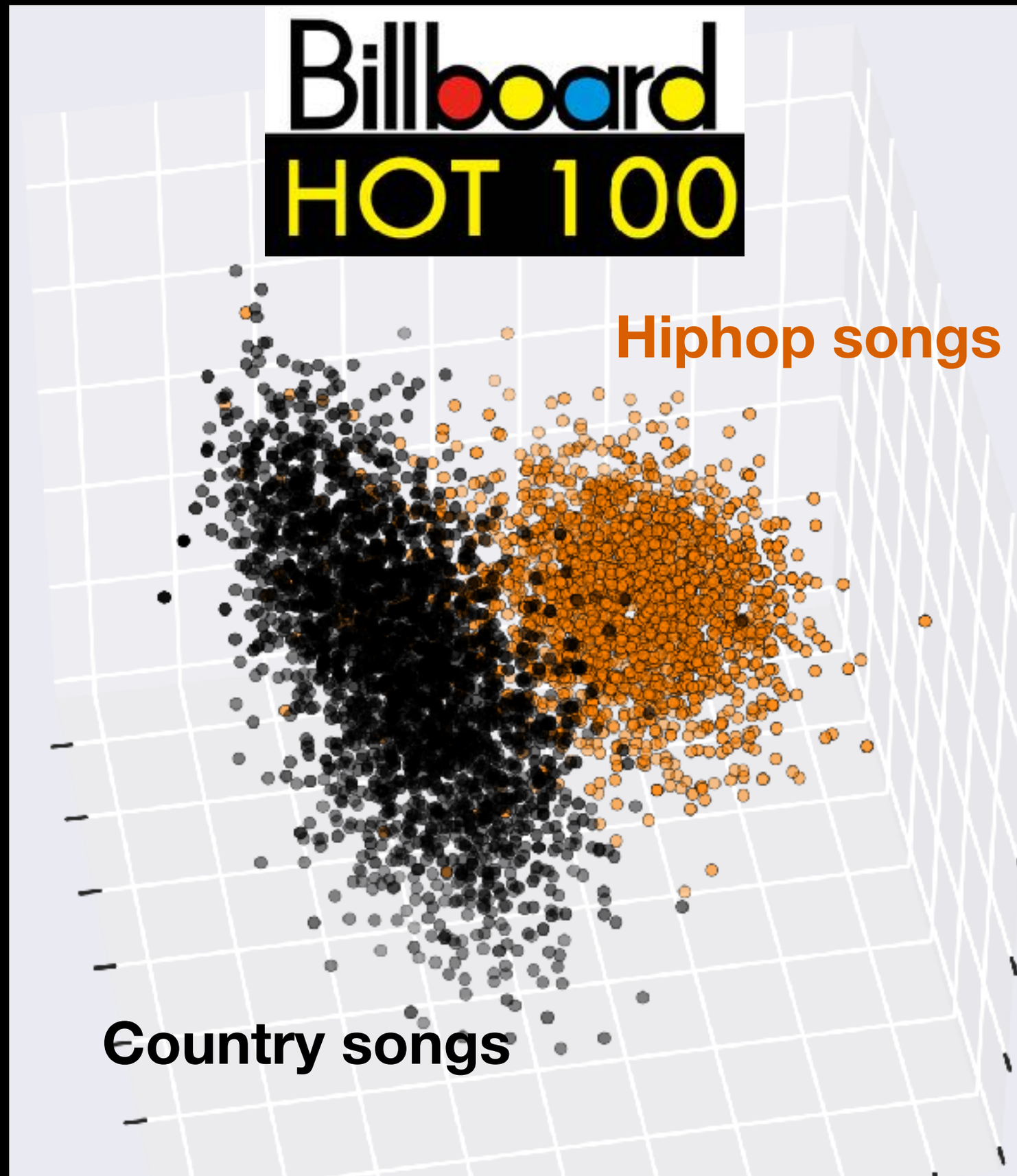
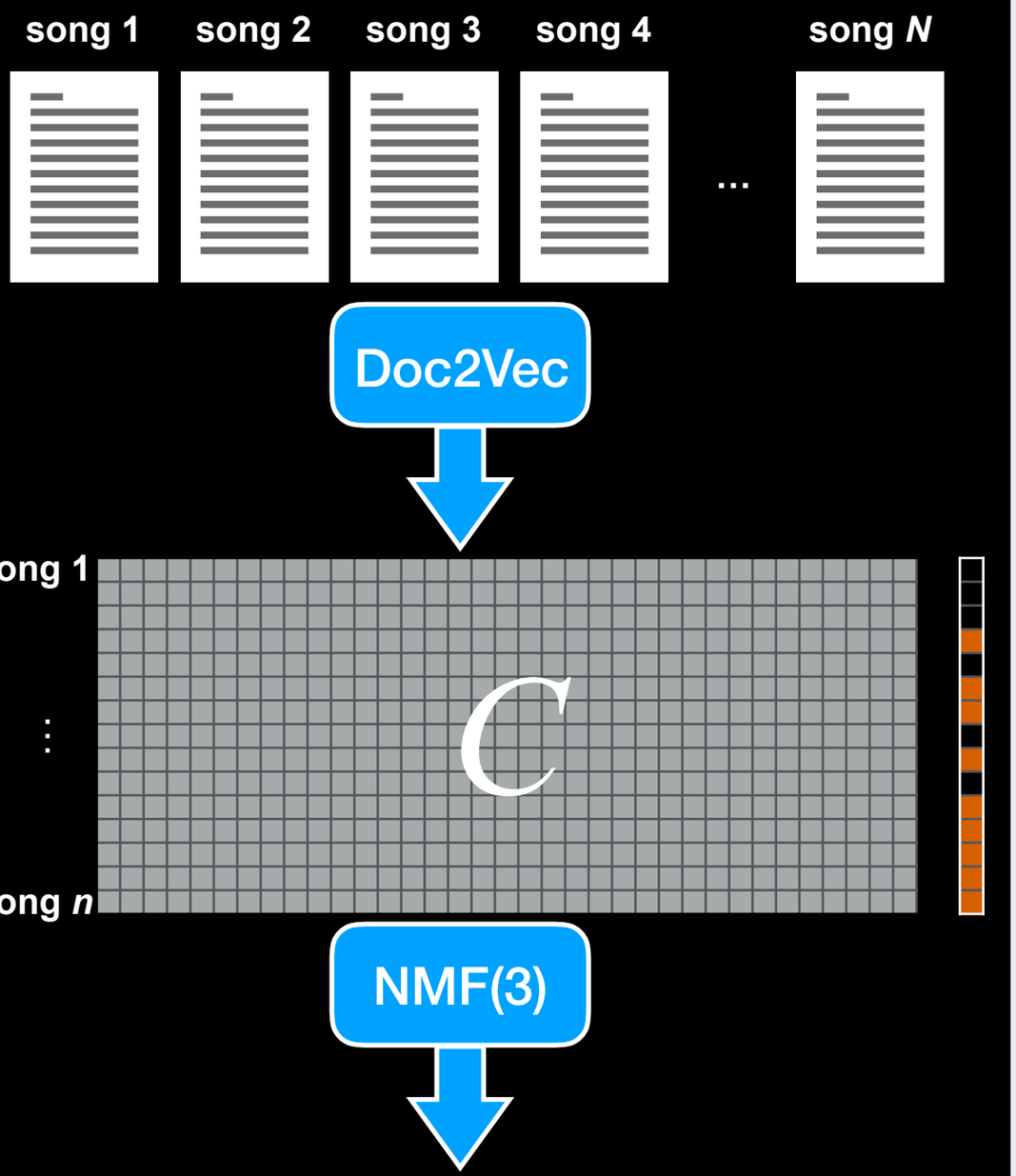
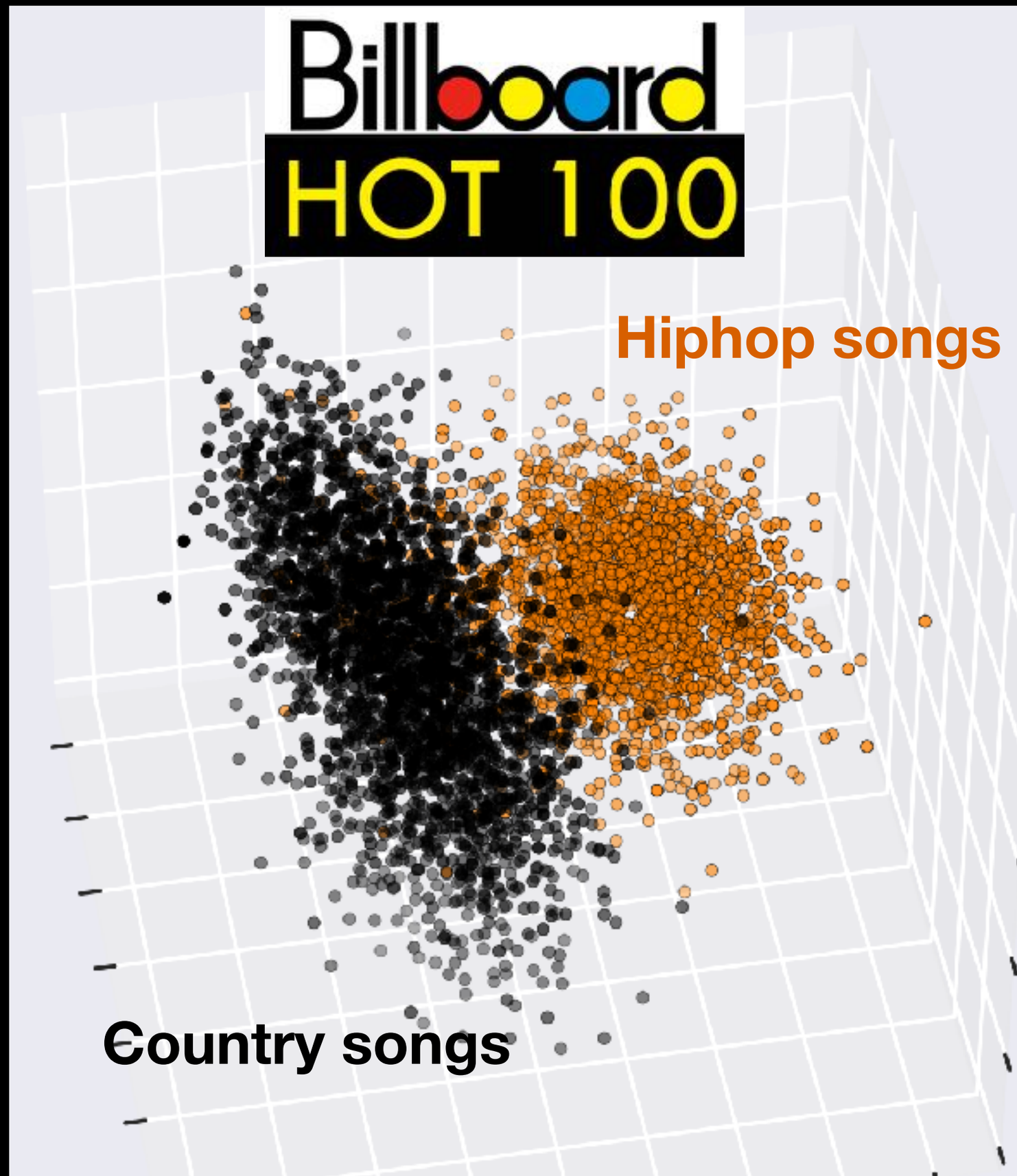




Dimensions as Coordinates





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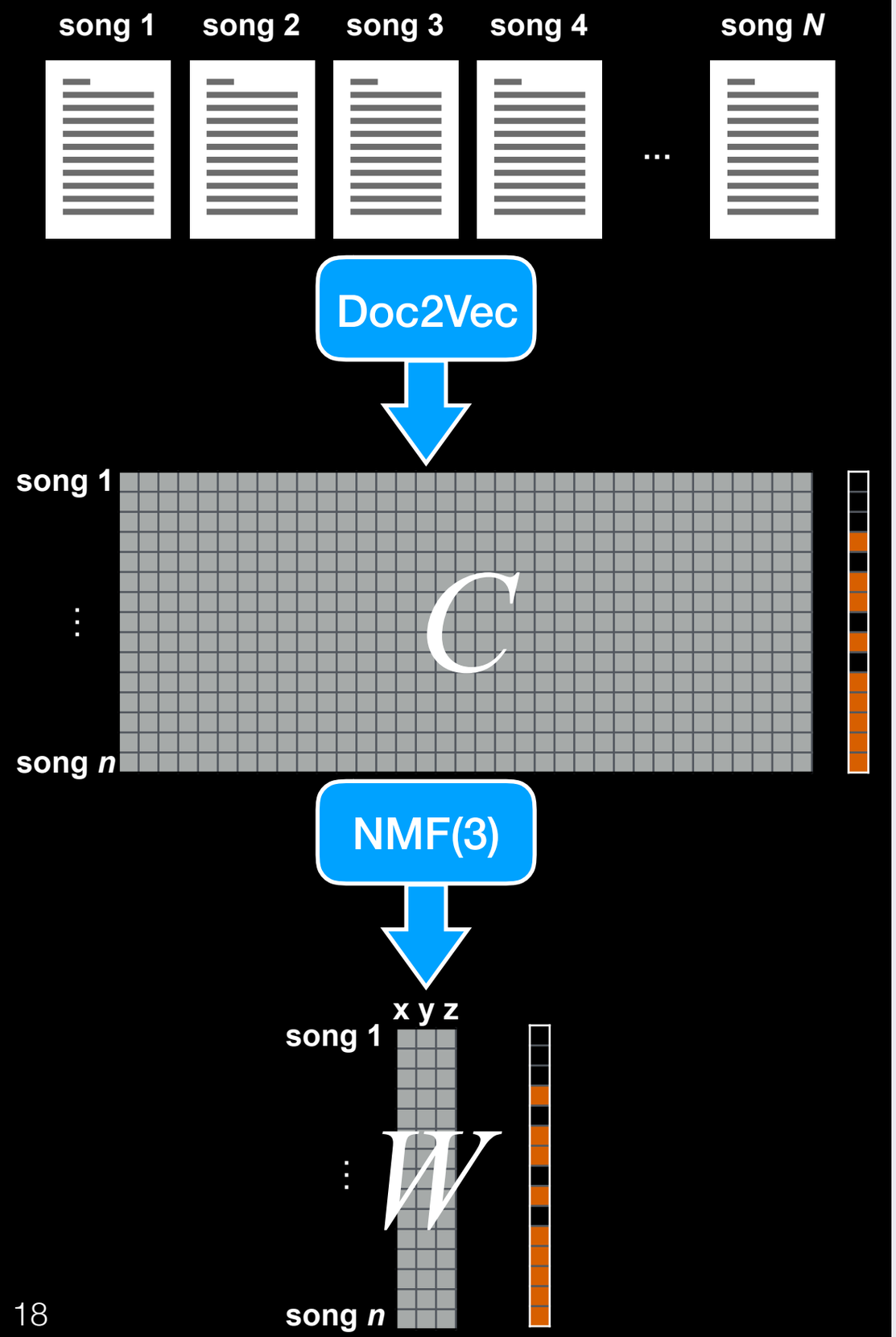
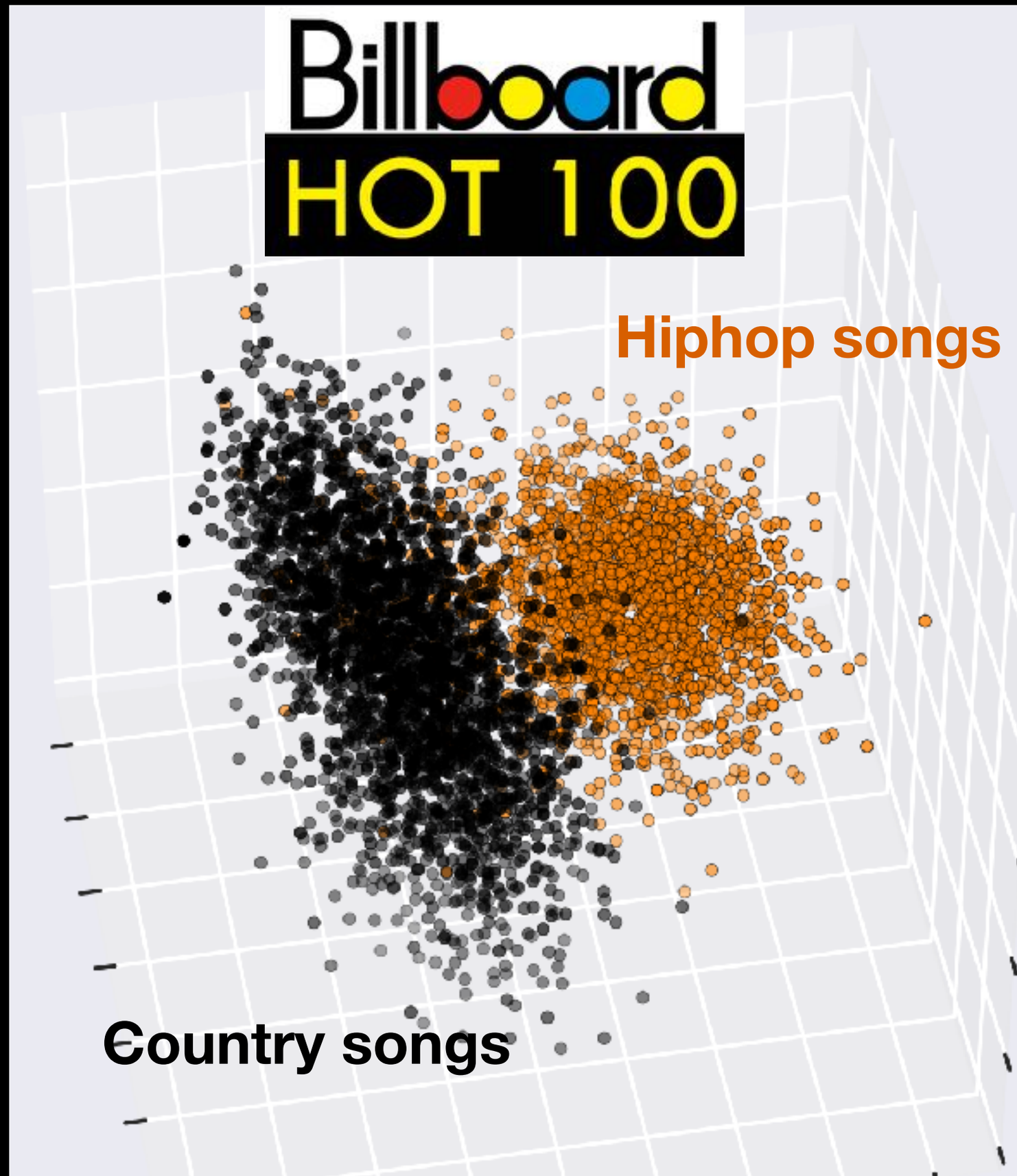




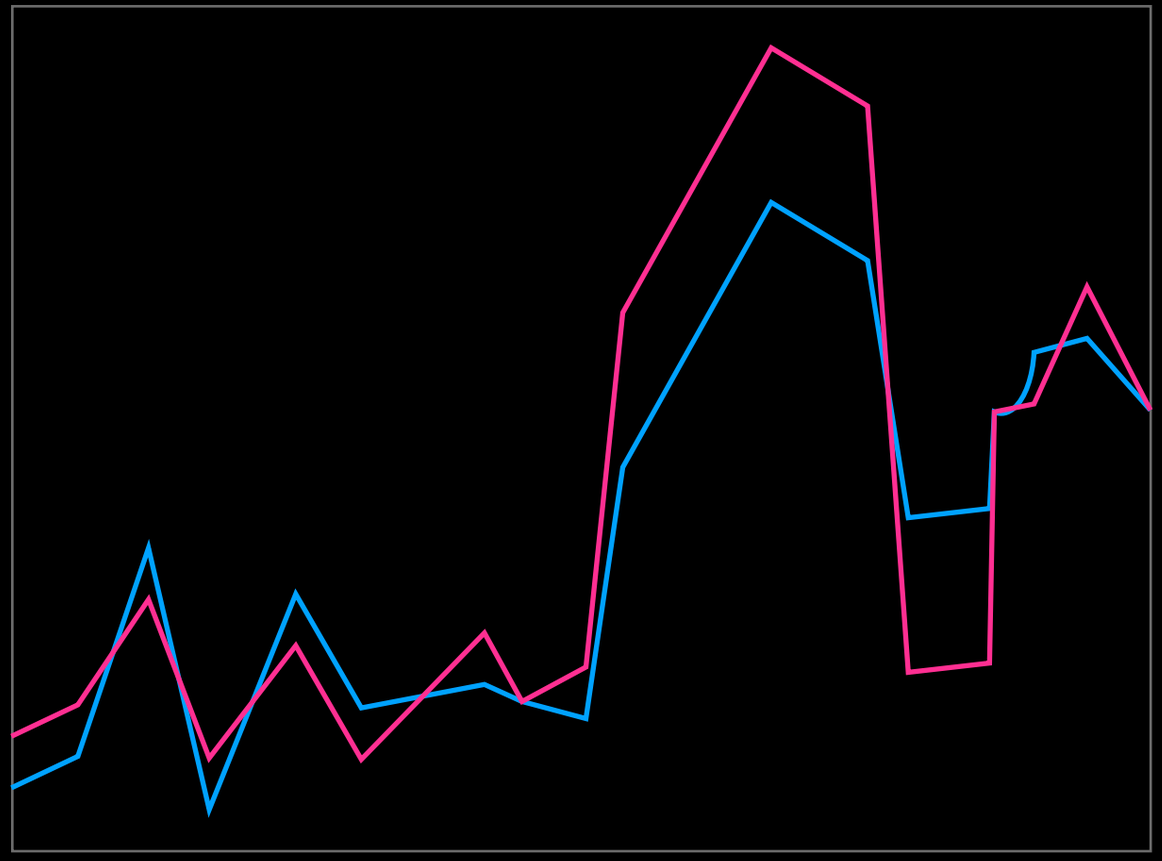
Van der Maaten & Hinton, 2008

t-SNE

- Map/preserve neighborhood structure of high-dimensional space in lower-dimensional space

- Minimize difference between probability distributions over neighbors in both dimensions

$P(n_j|n_i)$



Bocconi

Van der Maaten & Hinton, 2008

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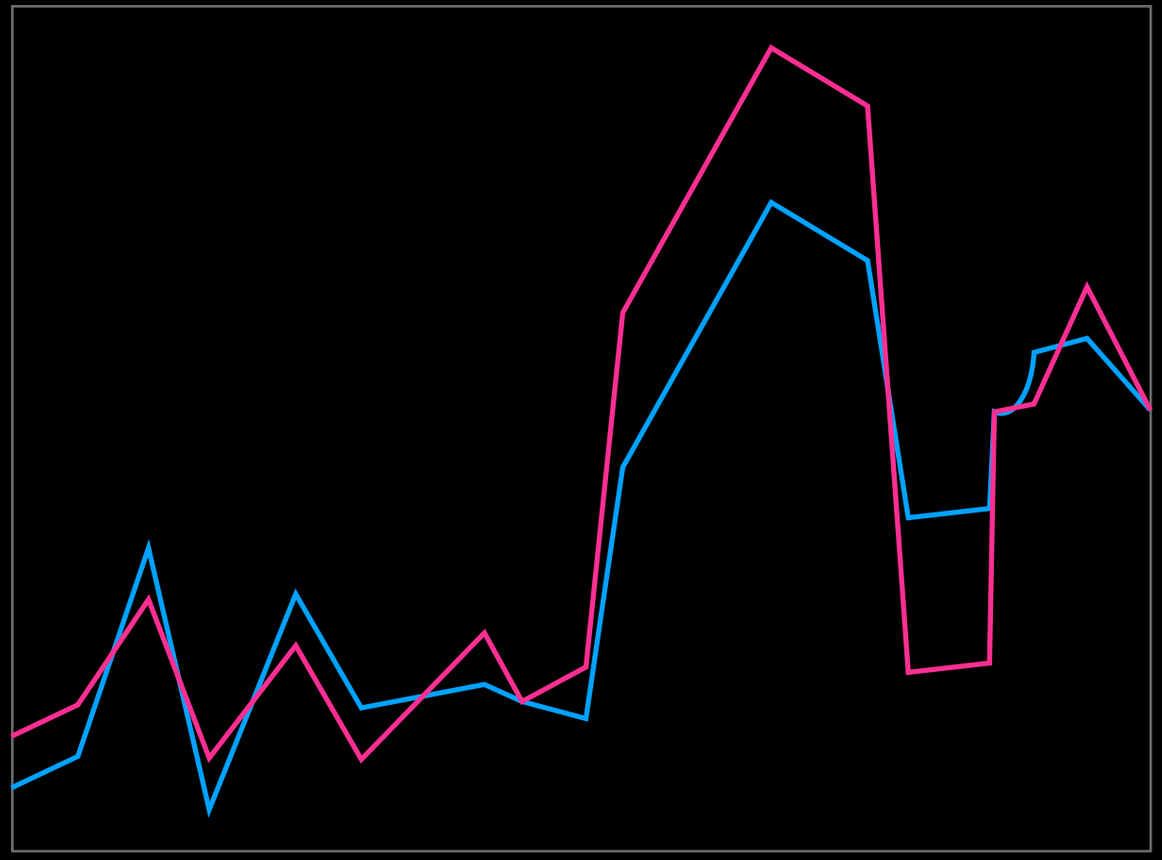
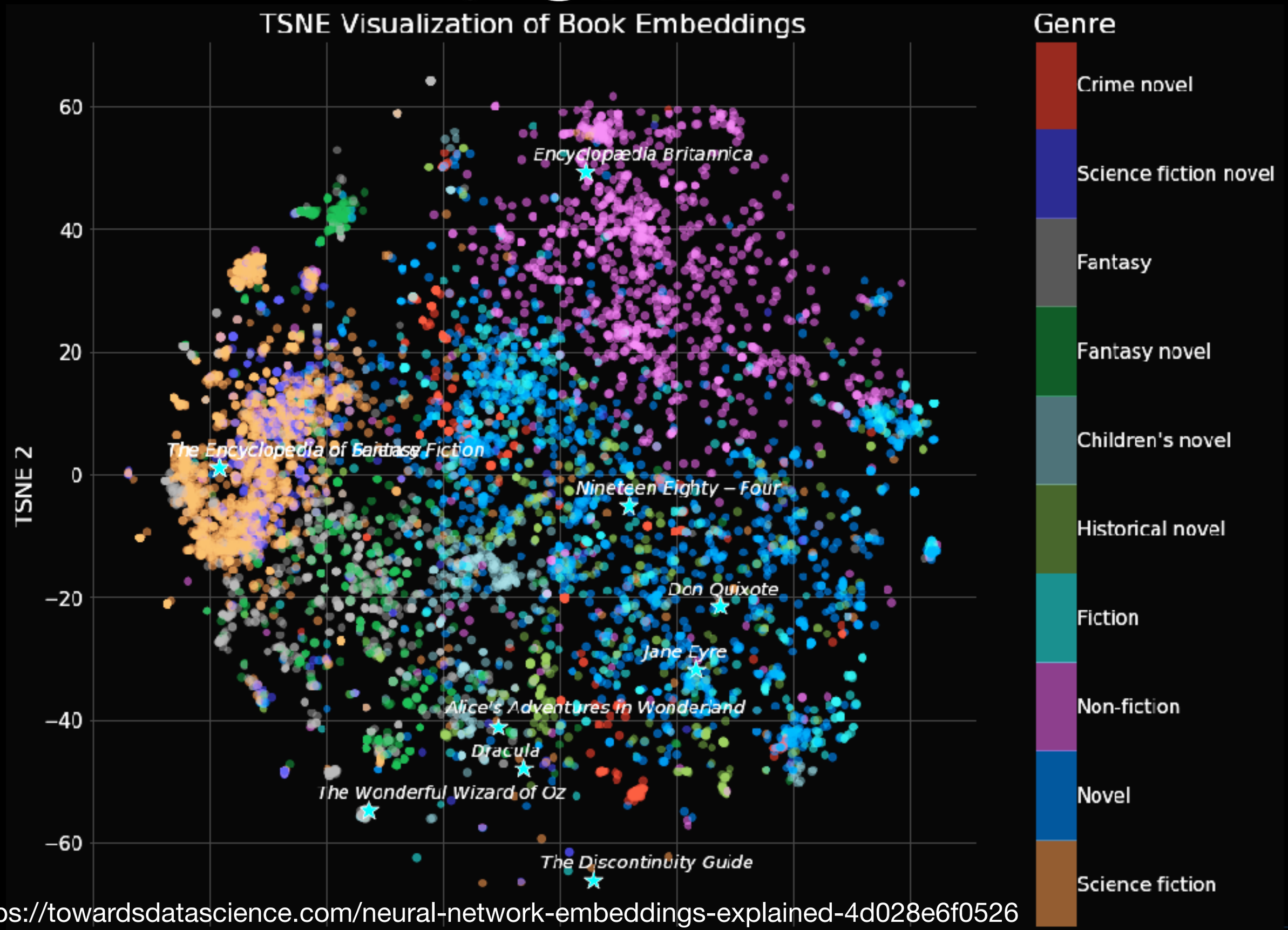


+ Nicer spatial images

– Stochastic (many runs)

– Many parameters

t-SNE



https://towardsdatascience.com/neural-network-embeddings-explained-4d028e6f0526

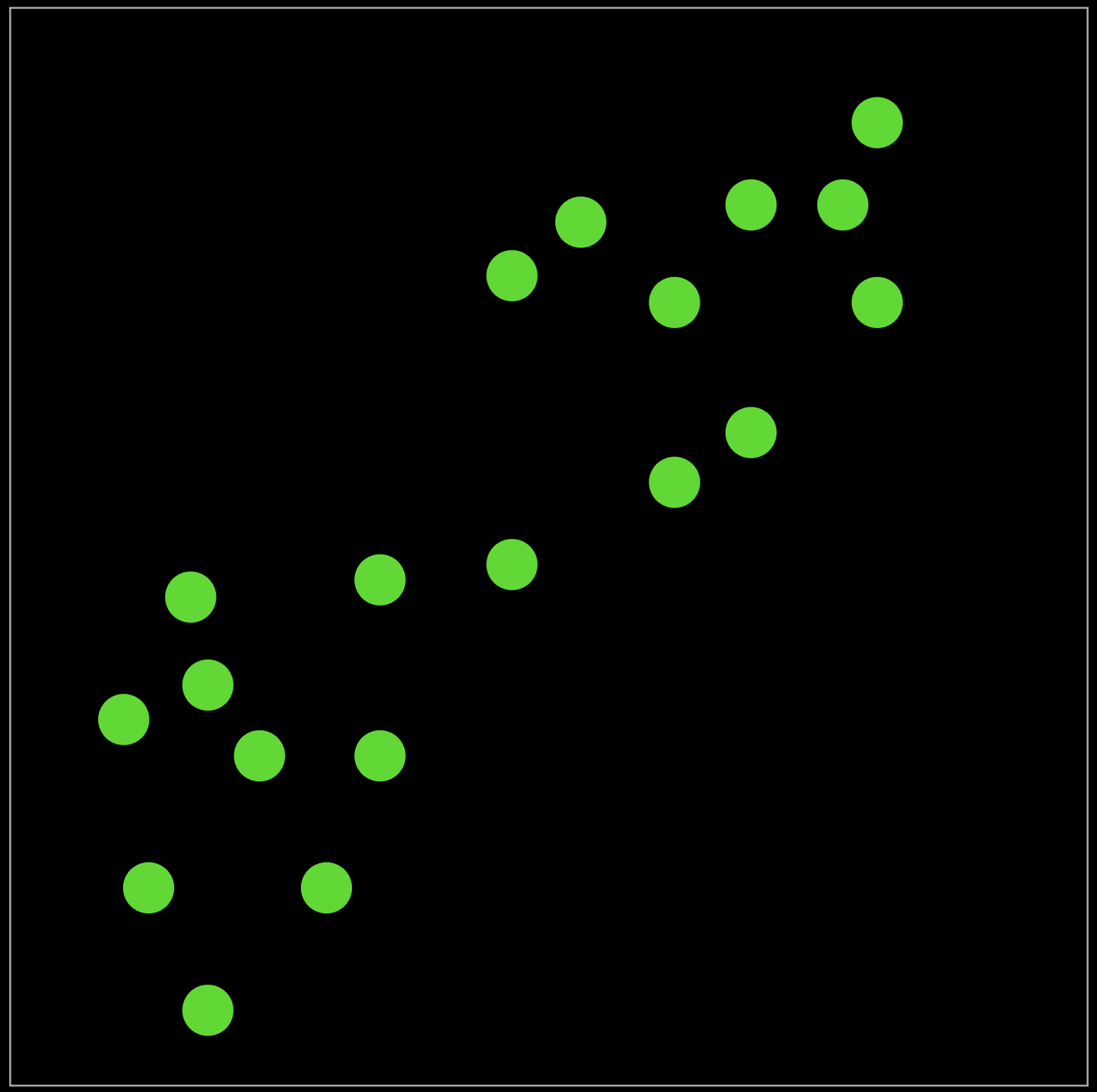
Clustering

Bocconi

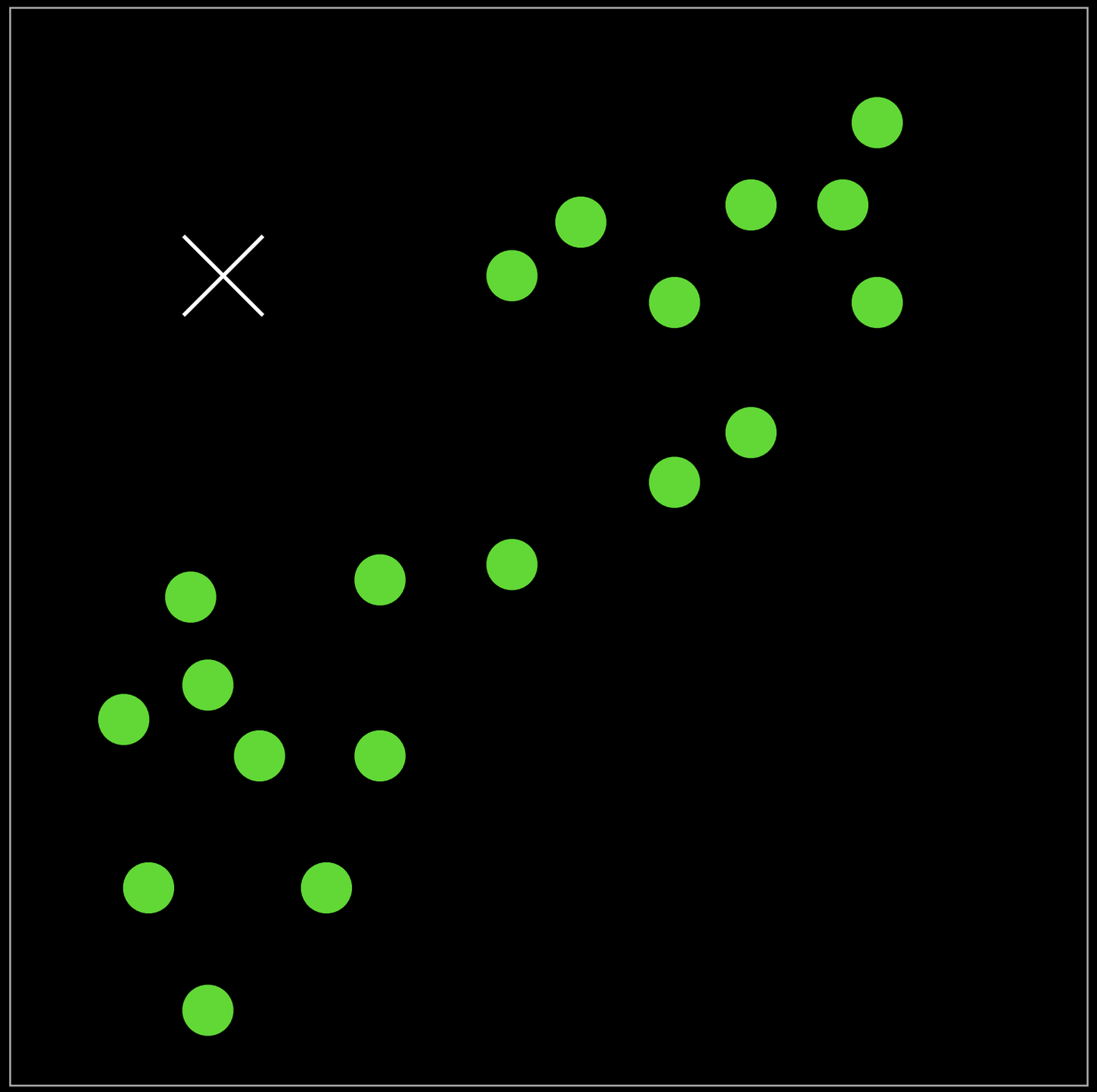
k-Means Clustering

Bocconi

k-Means



k-Means



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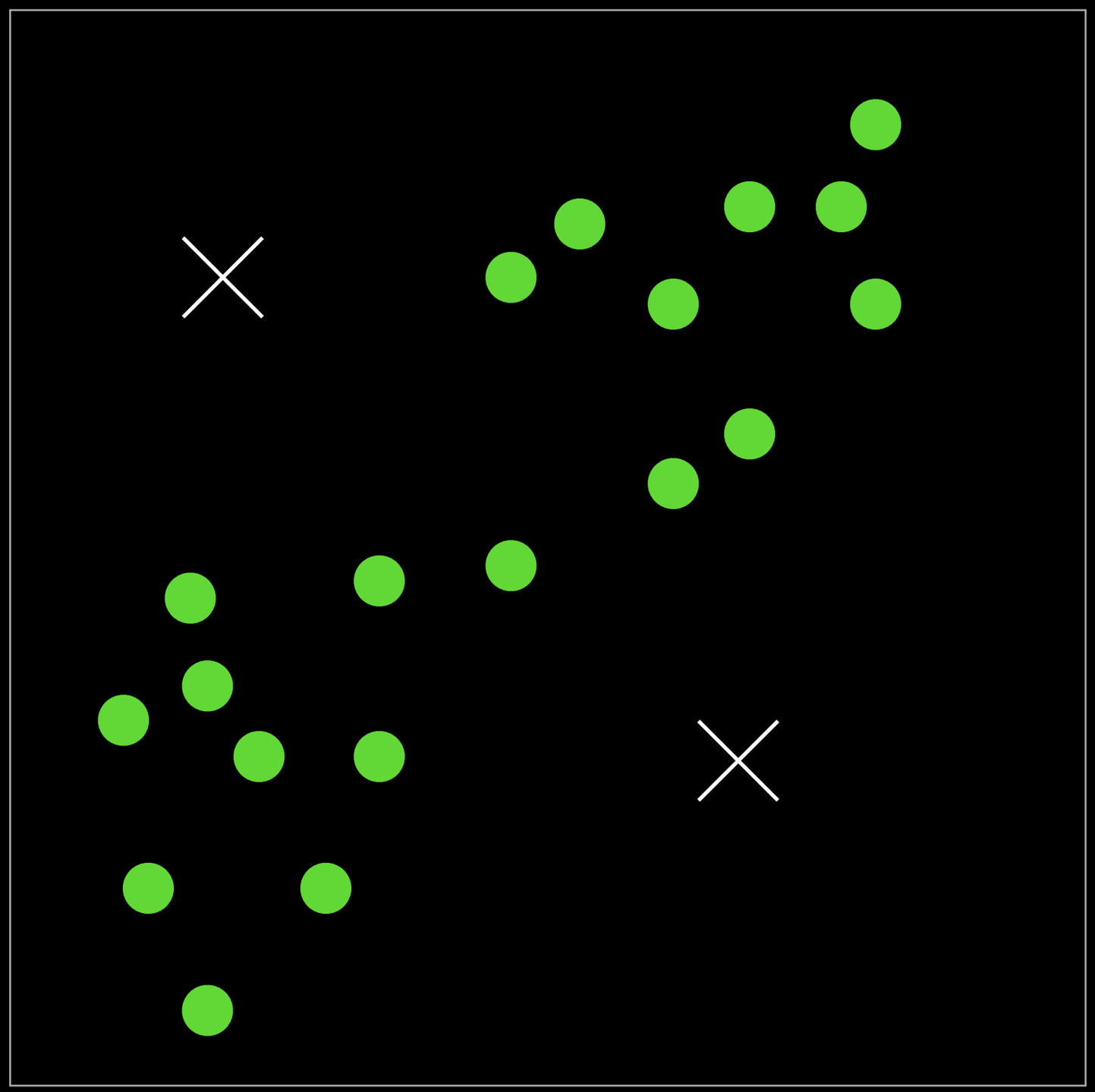

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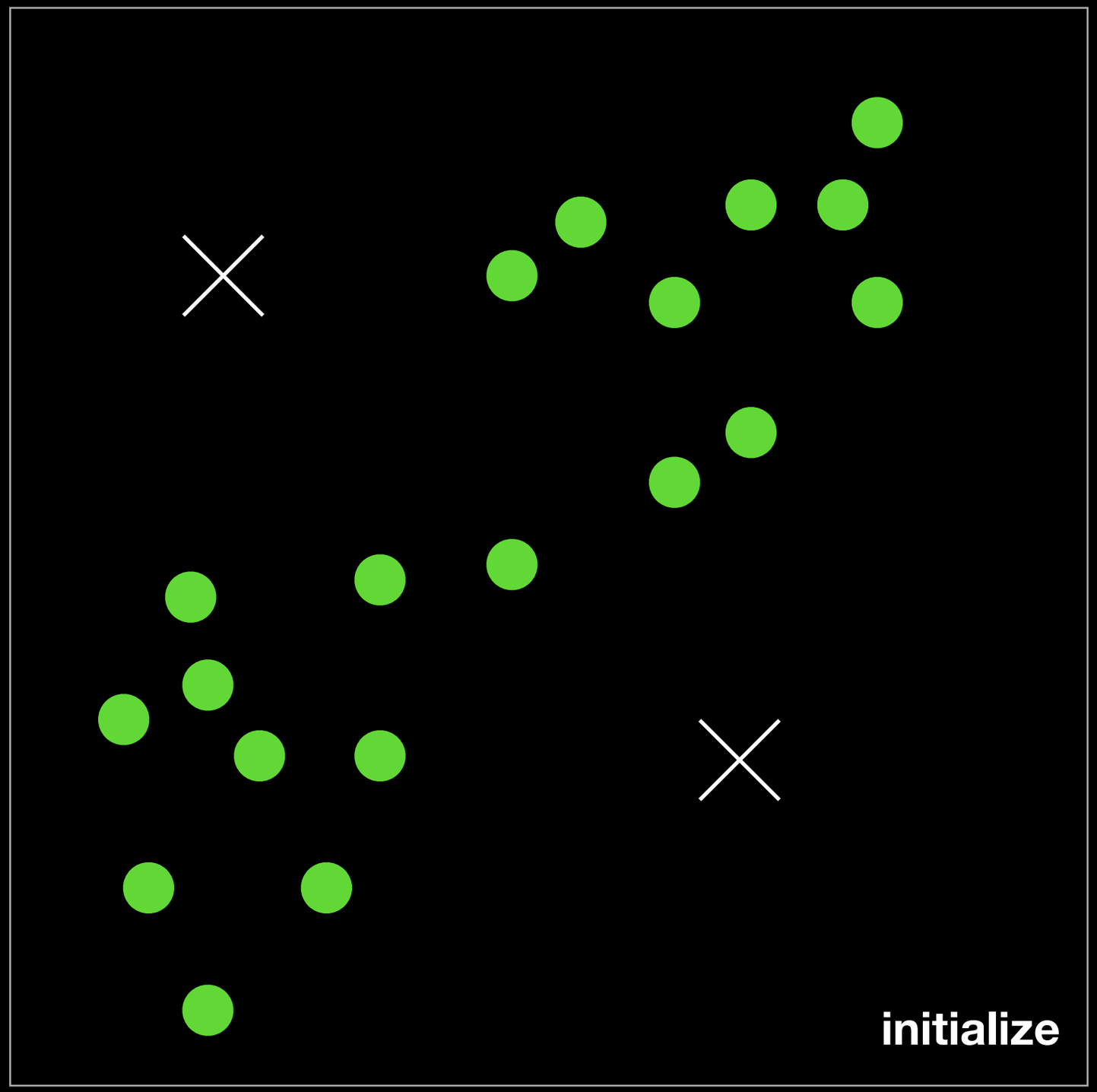

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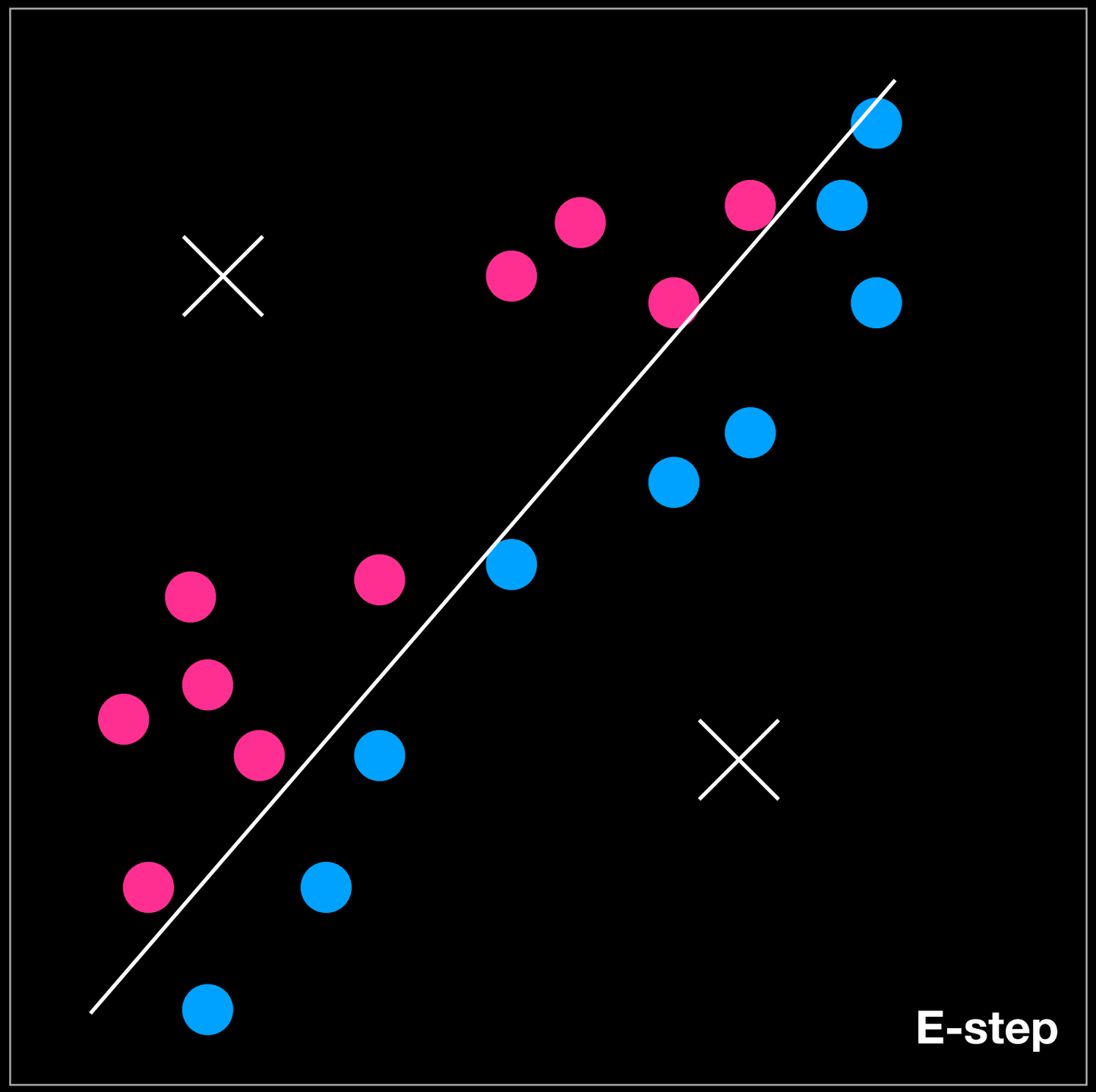
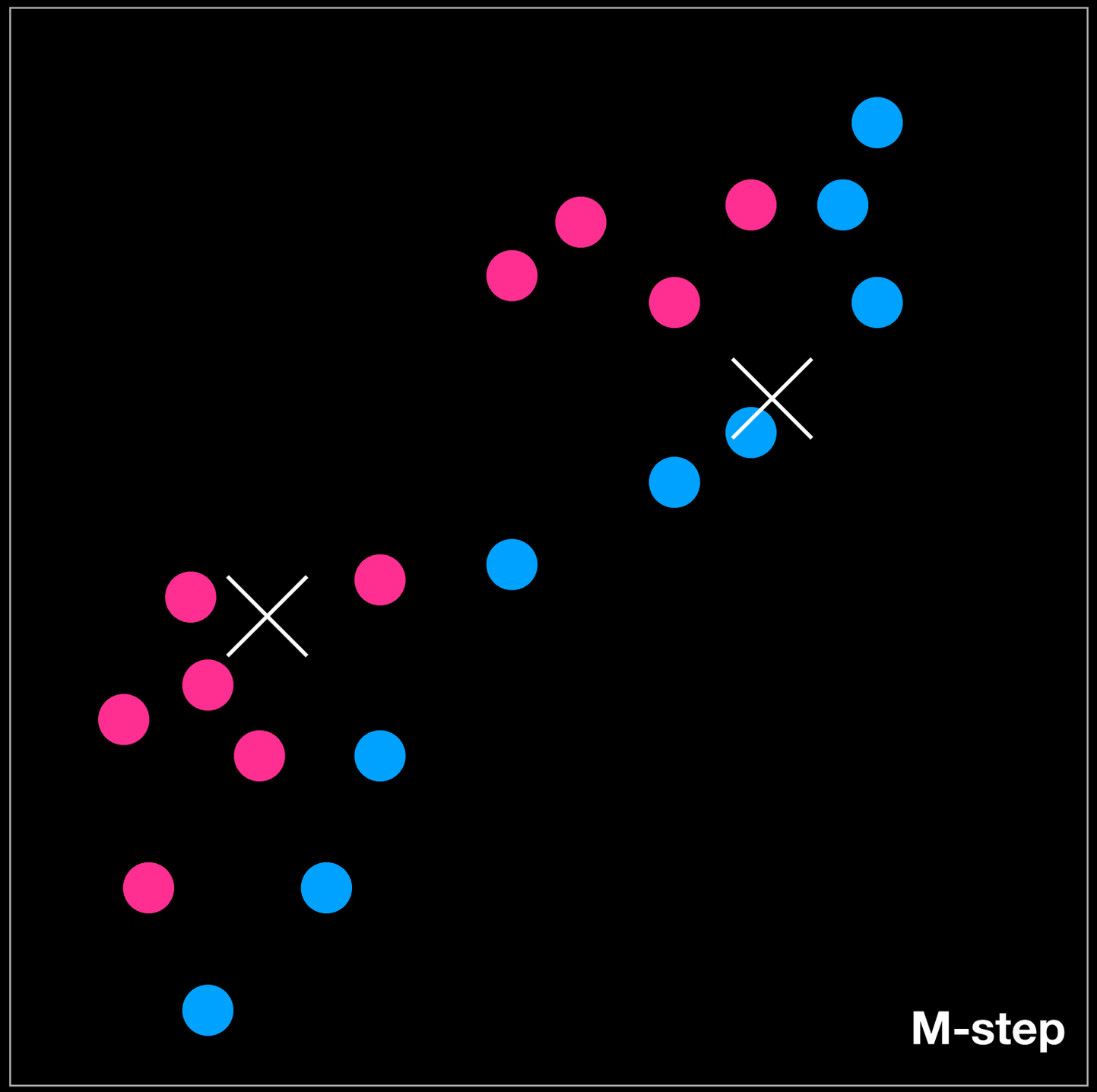


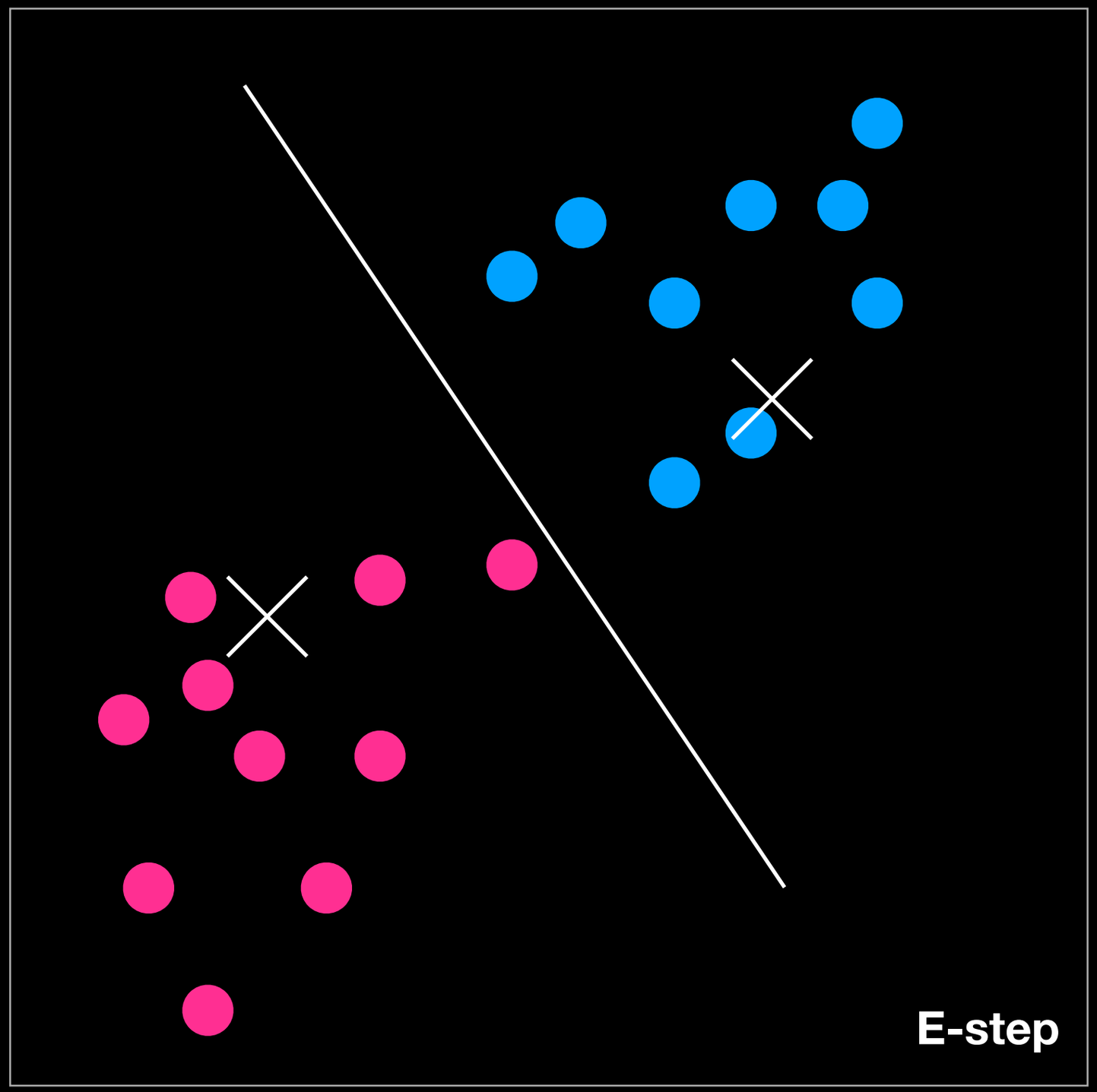
ASSIGN POINTS TO CENTROIDS

k-Means

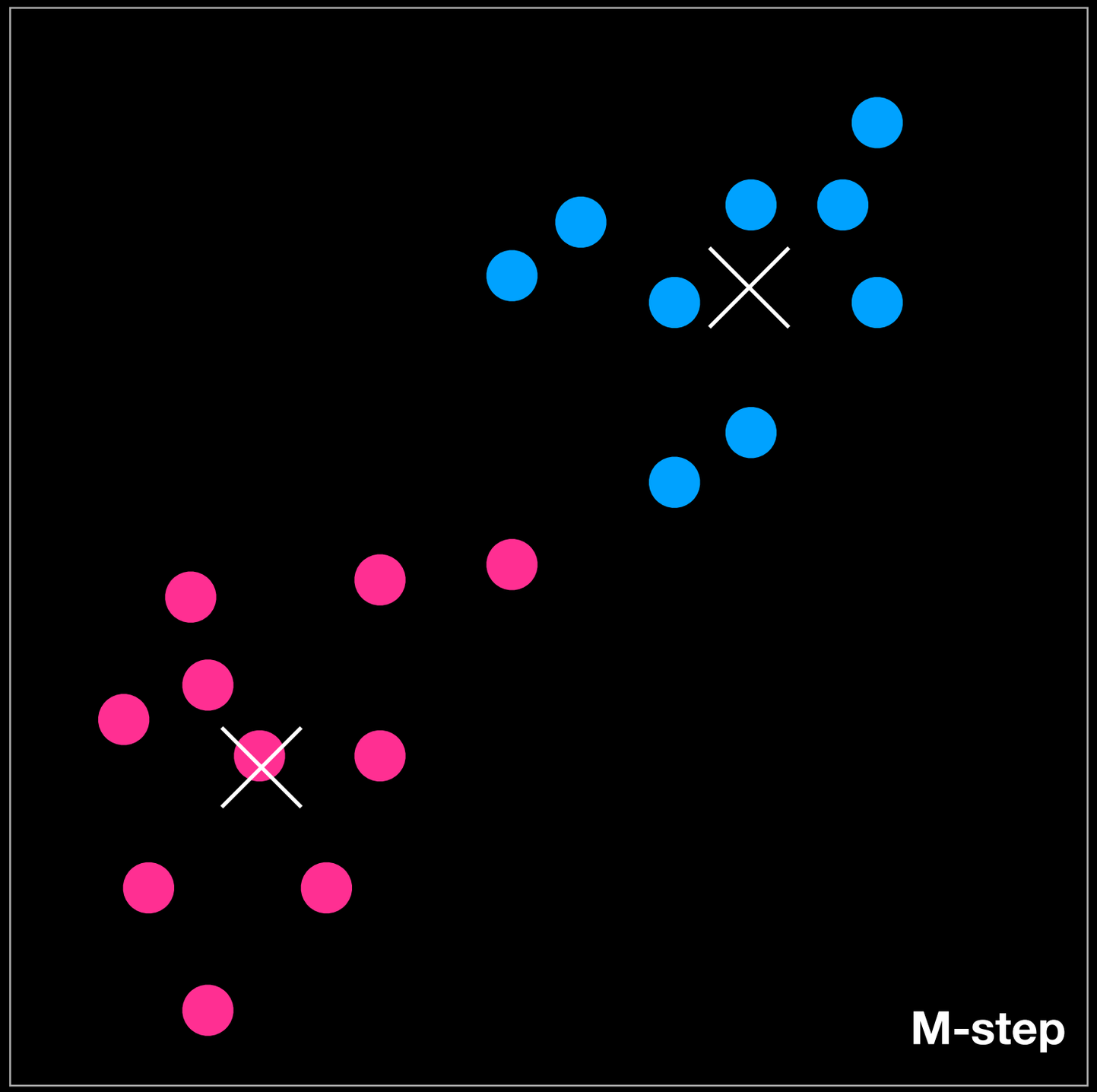


RECOMPUTE CENTROIDS

k-Means



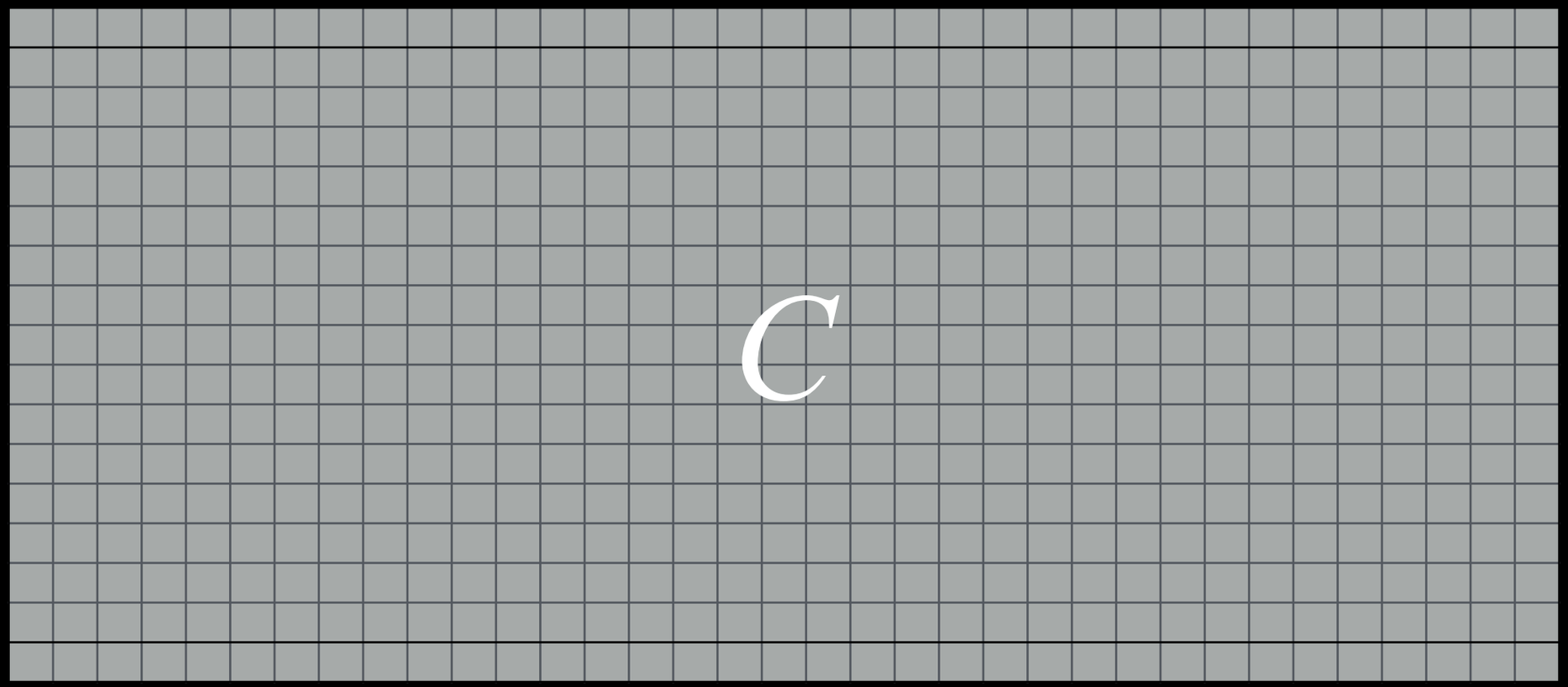
k-Means



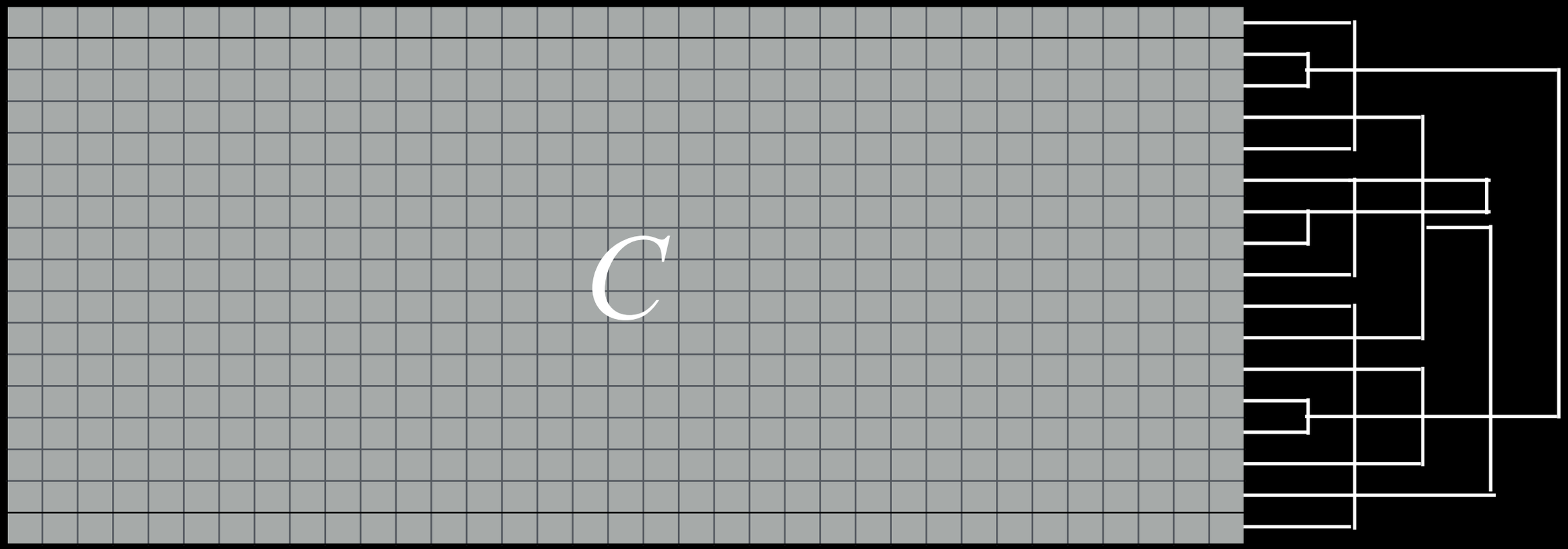
Agglomerative Clustering

Bocconi

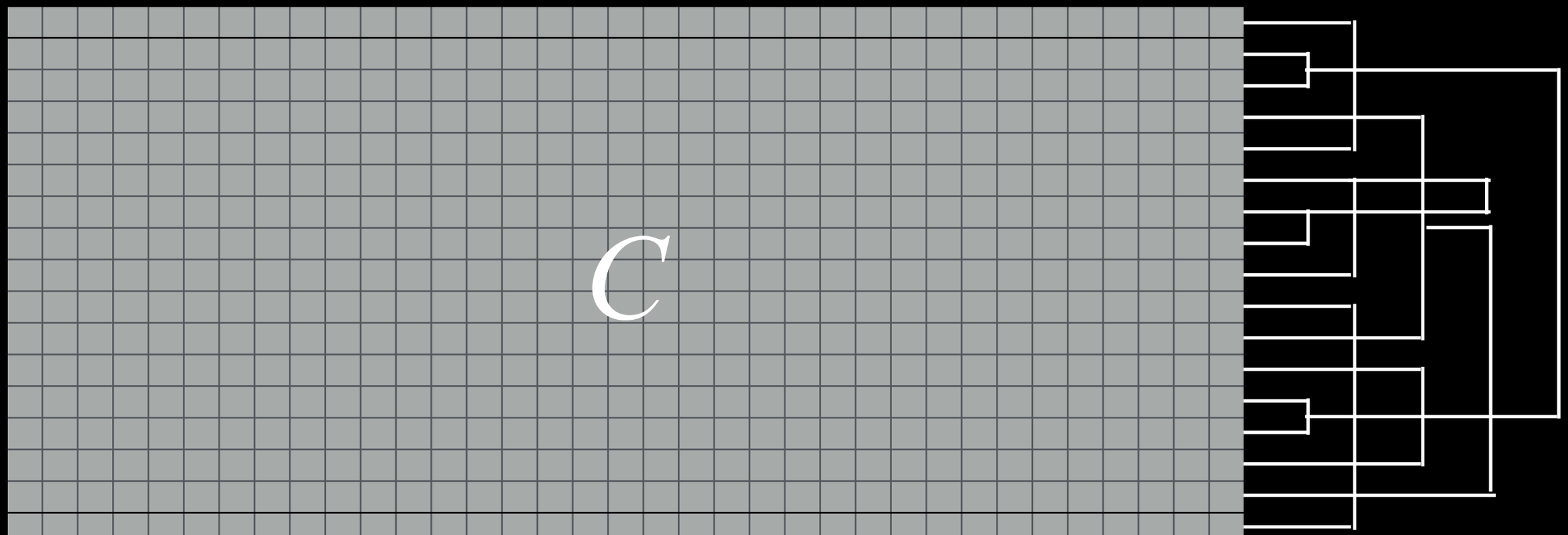
Building Up



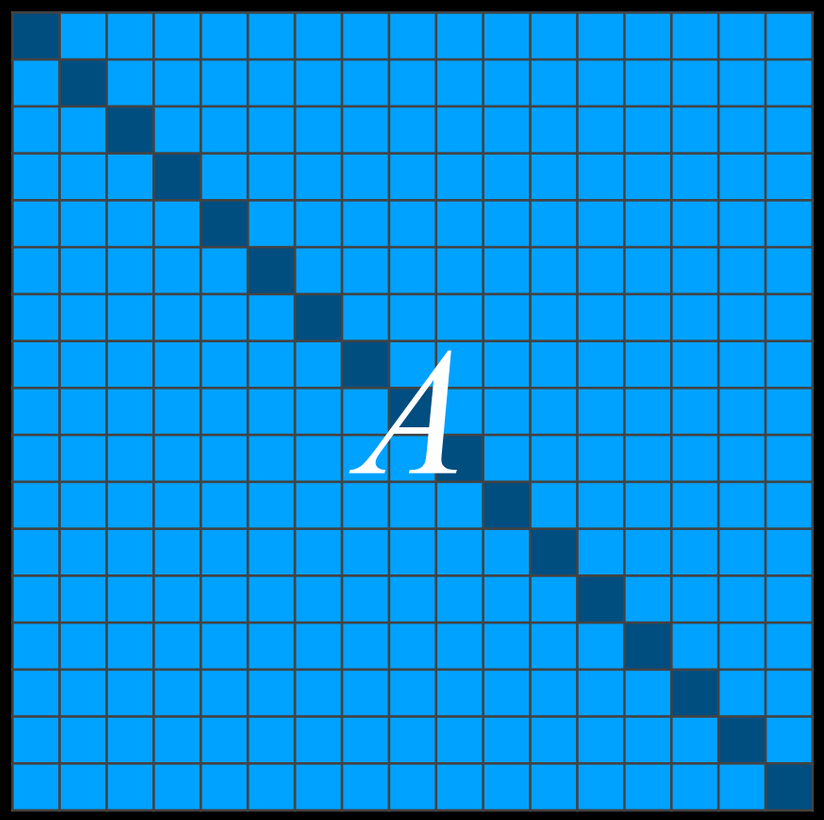
Building Up



Building Up

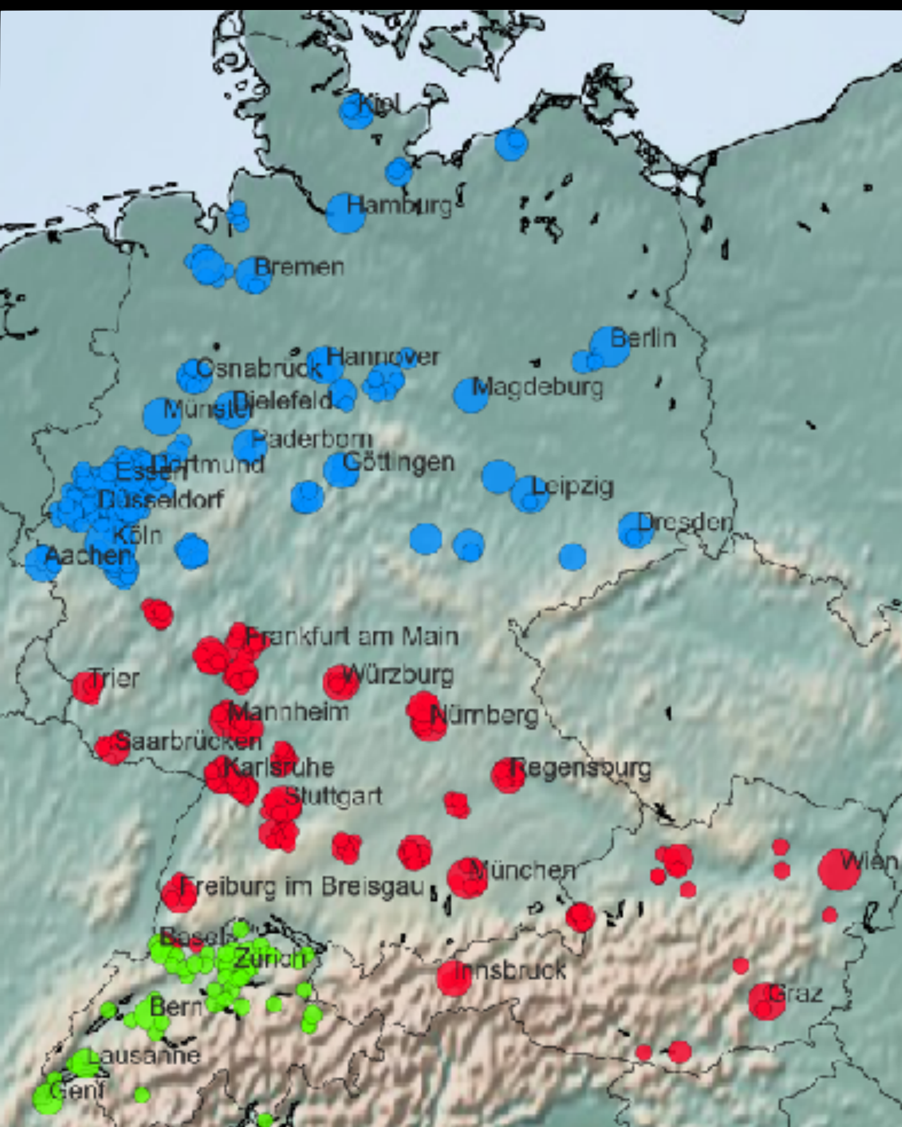


ADJACENCY MATRIX



Dialect Clusters

3



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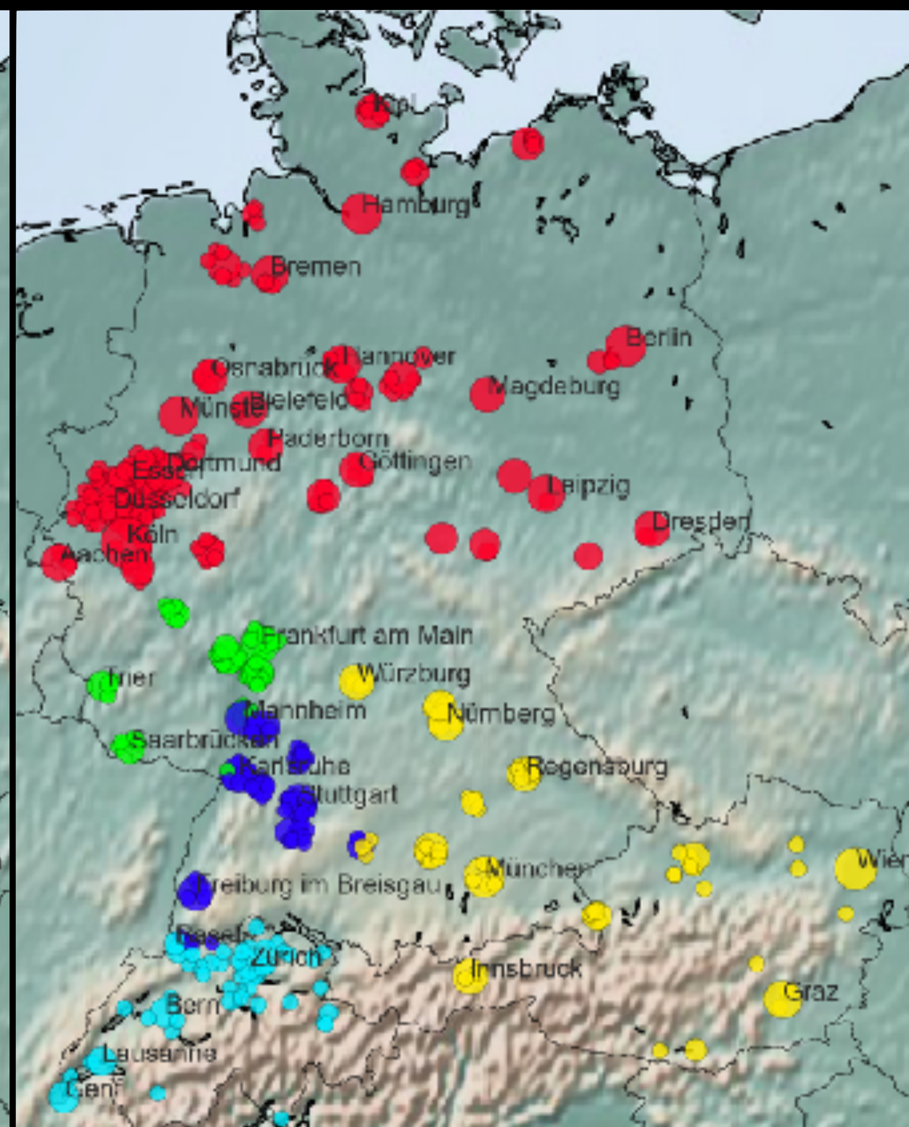

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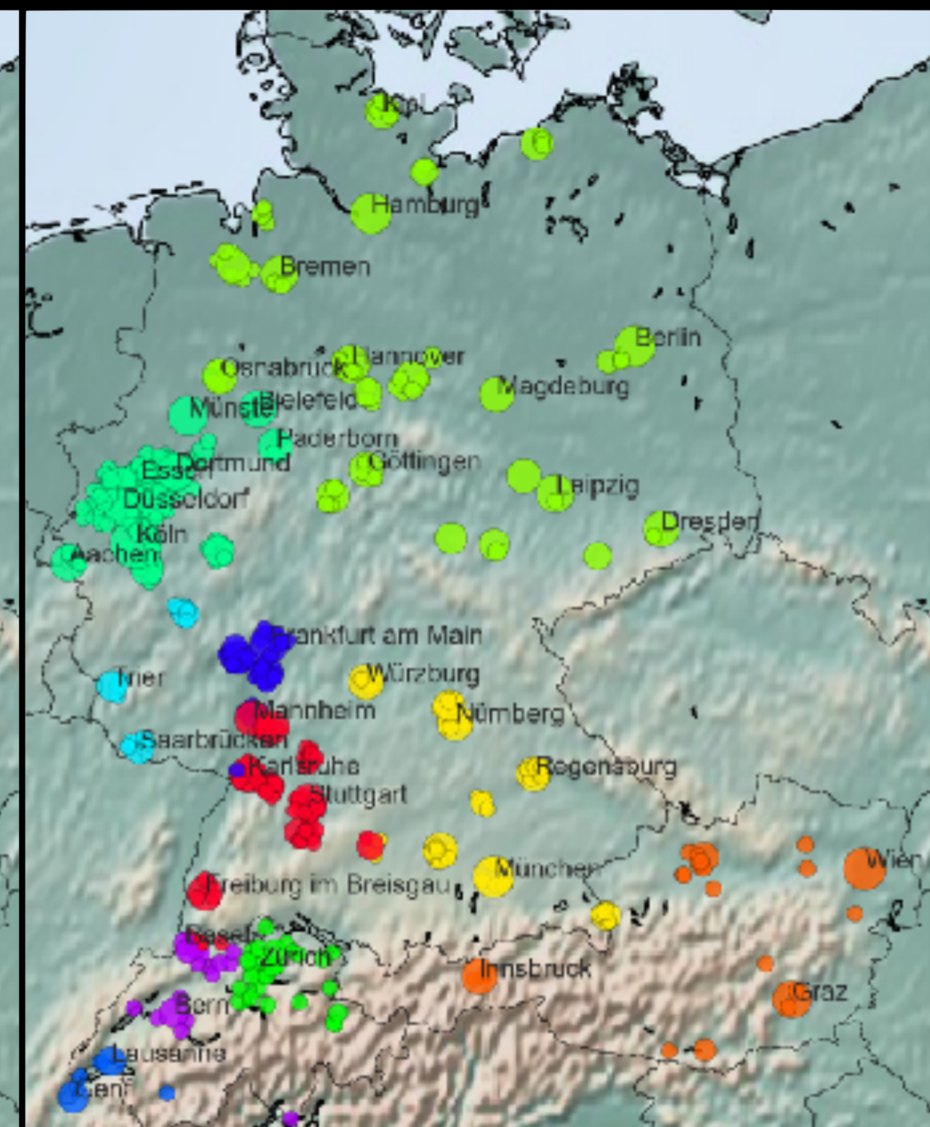

Bocconi

Evaluating Clusters

Bocconi

Making Sense of Clusters

perspicacious

lacerate

president

kissed

fresh

induce

rotten

platypus

arsenic

mortify

mortgage

recognize

pie

blue

Making Sense of Clusters

president
platypus
pie
mortgage

recognize
induce
mortify
kissed
lacerate

rotten
perspicacious
fresh
blue
arsenic

Making Sense of Clusters

NOUNS

president

platypus

pie

mortgage

VERBS

recognize

induce

mortify

kissed

lacerate

rotten

perspicacious

fresh

blue

arsenic

ADJECTIVES

Making Sense of Clusters

blue

induce

president

platypus

arsenic

pie

mortify

rotten

recognize

lacerate

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perspicacious

mortgage

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Making Sense of Clusters

blue

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mortify

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lacerate

mortgage

Bocconi

Making Sense of Clusters

mortify
induce
president
arsenic
platypus
recognize
perspicacious
lacerate
mortgage

blue
kissed
pie
fresh
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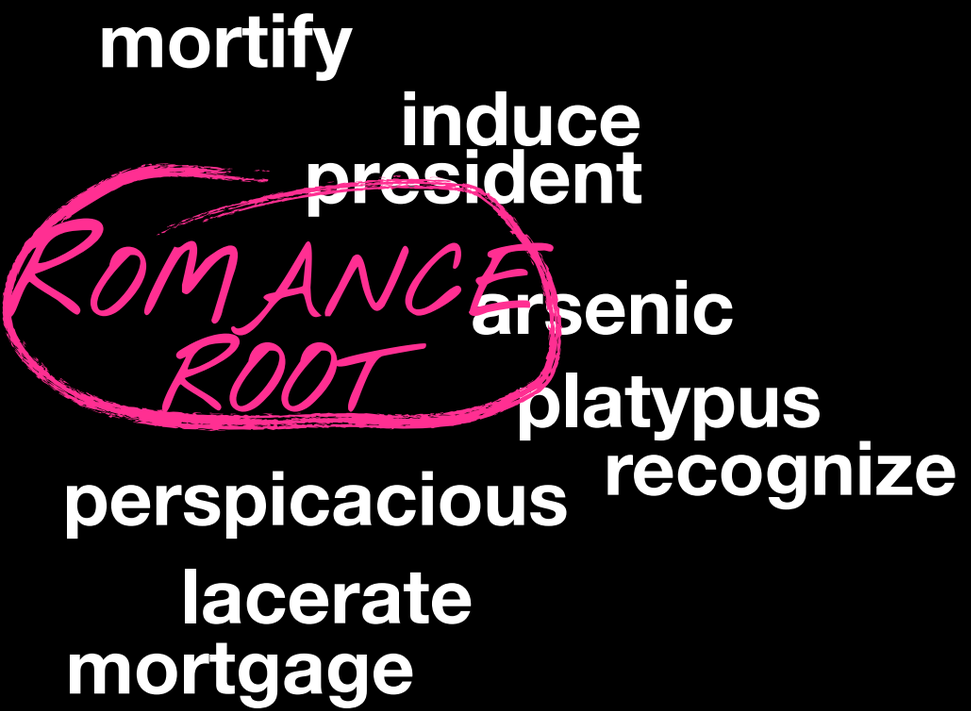
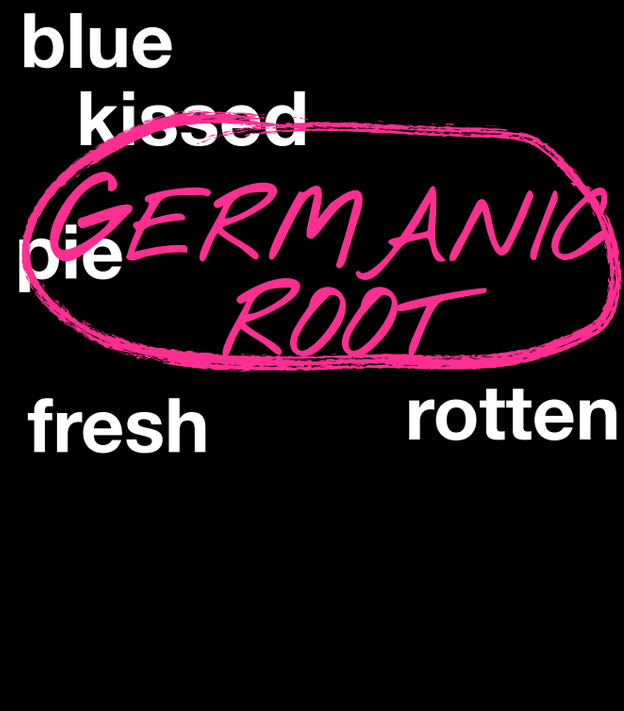
Making Sense of Clusters

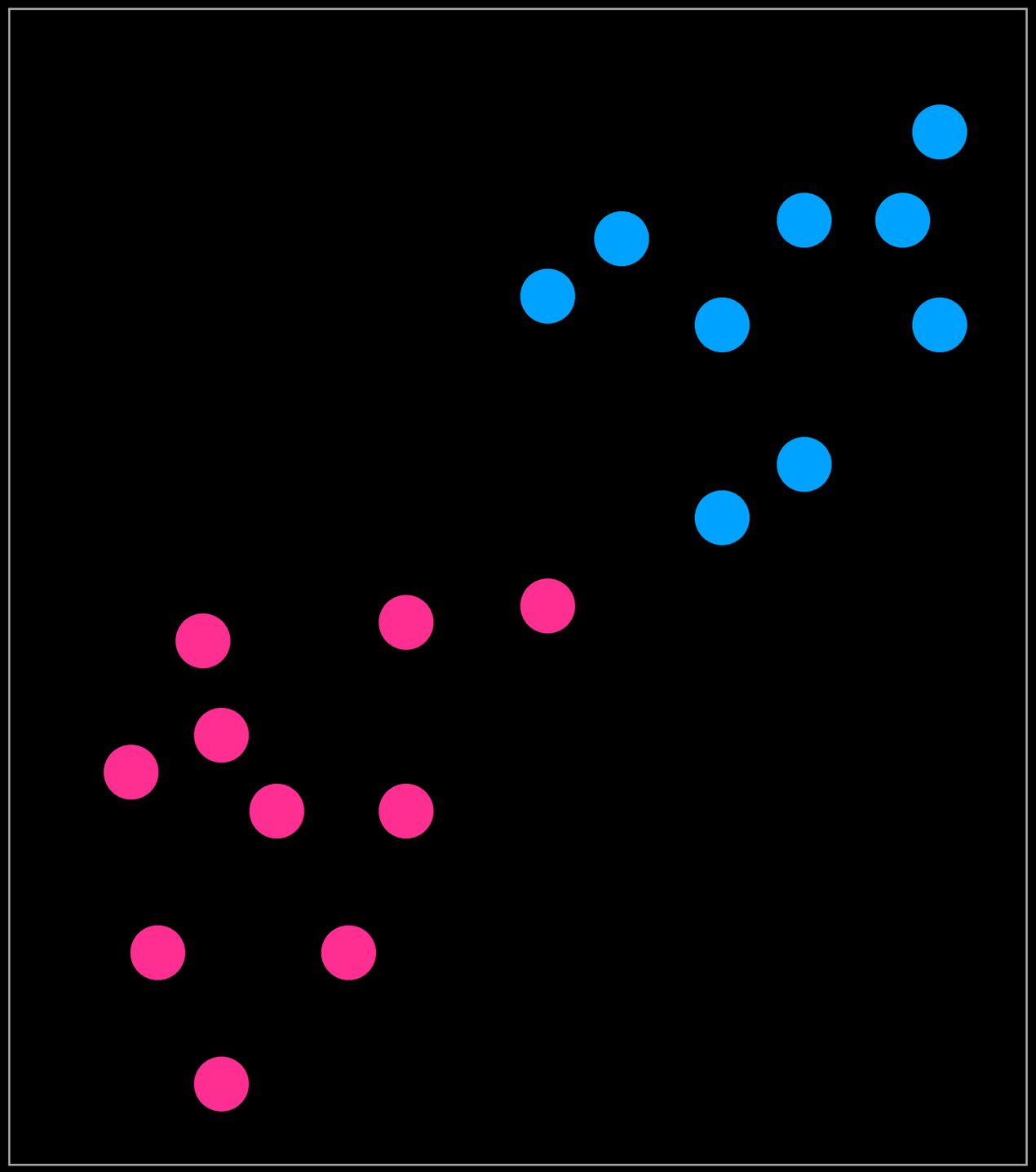




Making Sense of Clusters

Bocconi

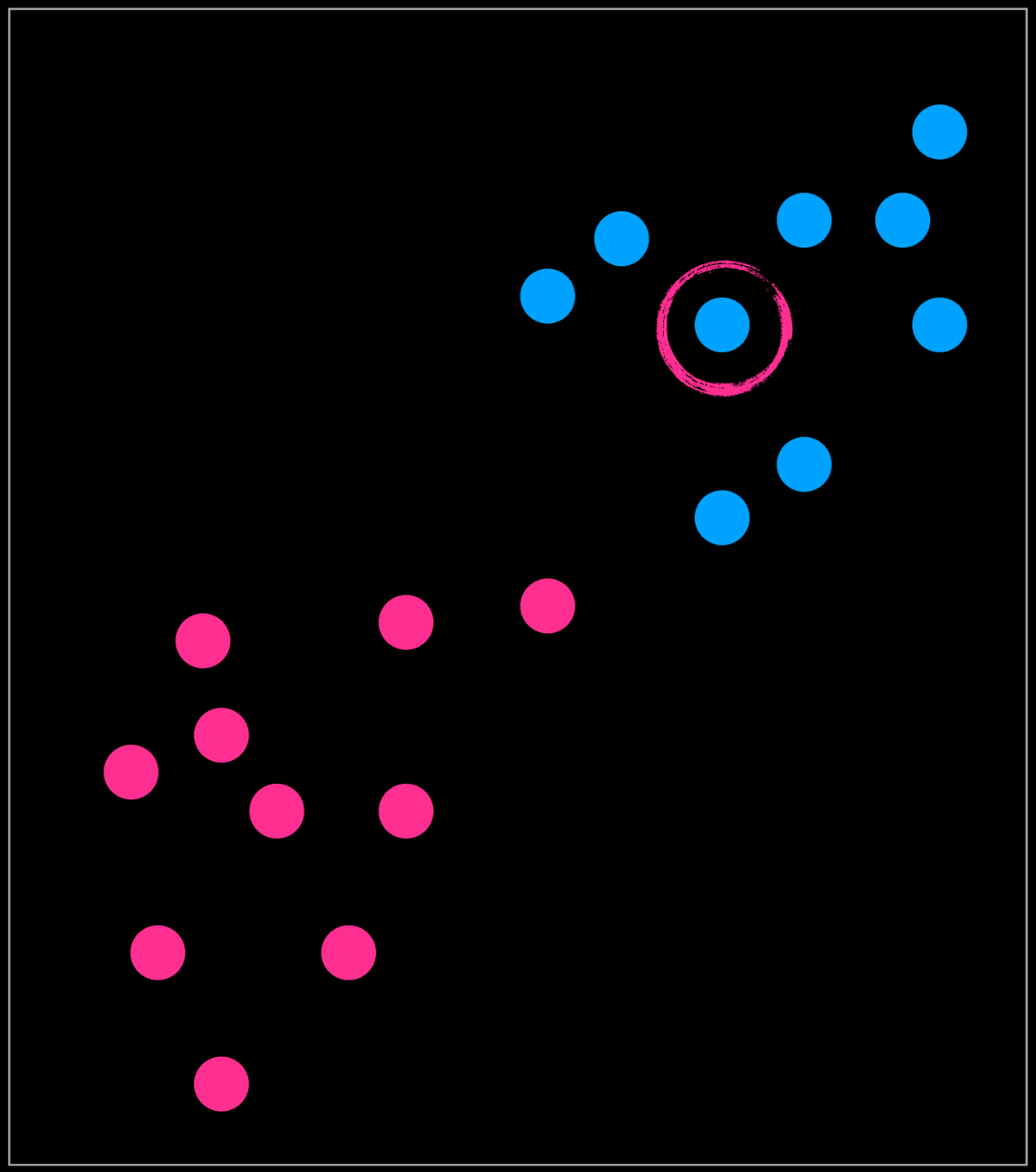
How Many Clusters?



Silhouette Score

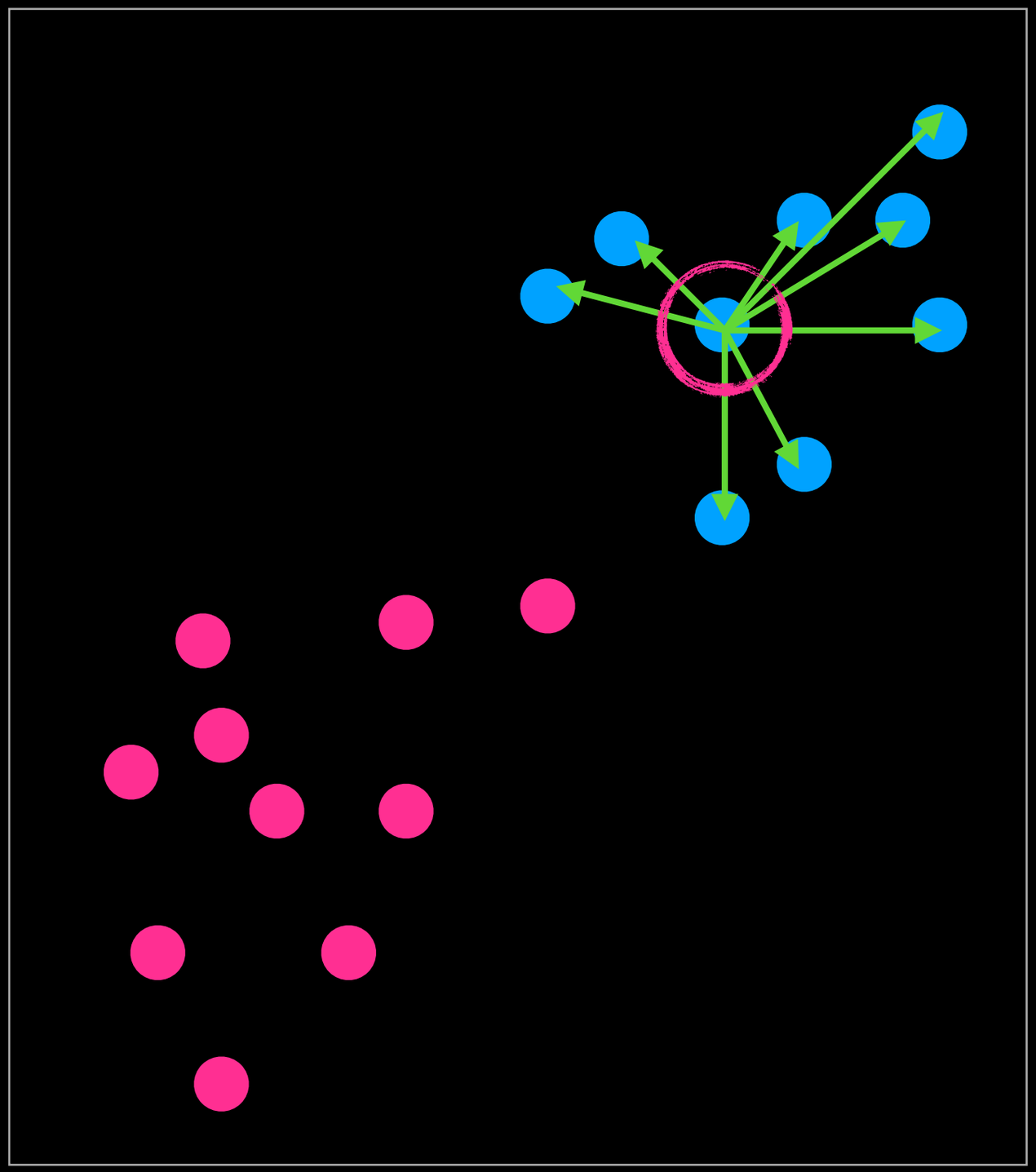
How Many Clusters?

Silhouette Score

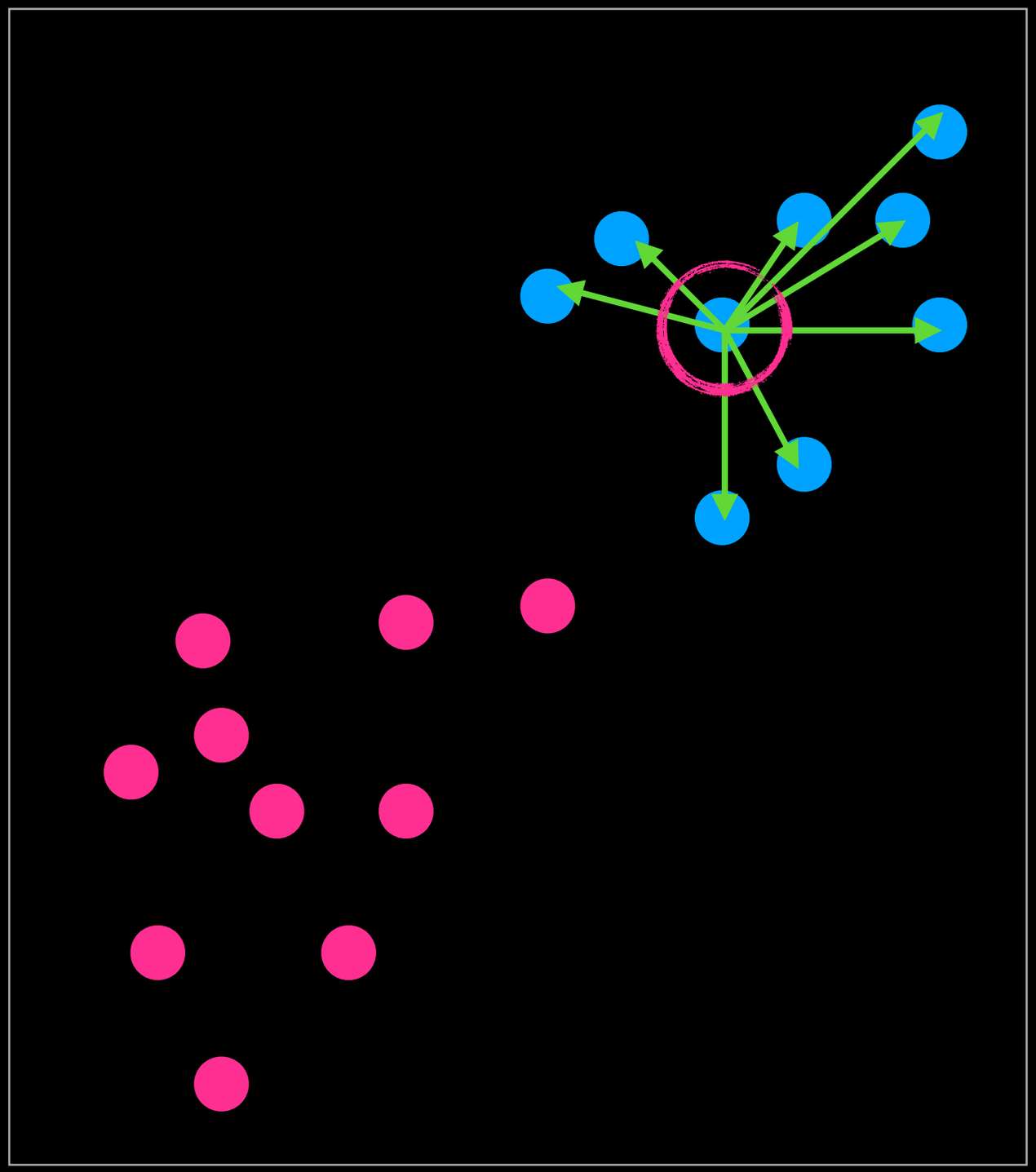


How Many Clusters?

Silhouette Score



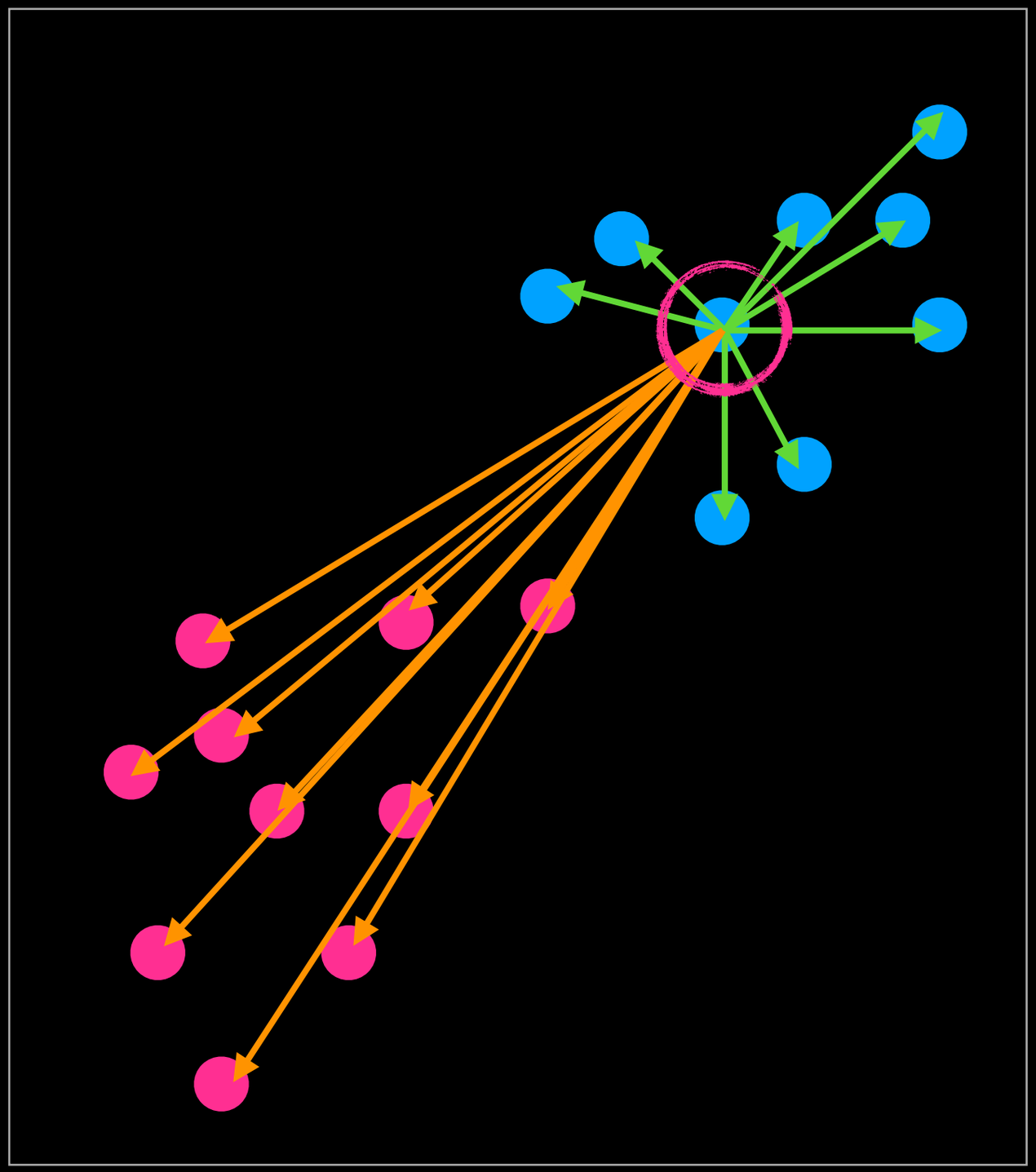
How Many Clusters?



Silhouette Score

a = *mean intra-cluster distance*

How Many Clusters?



Silhouette Score

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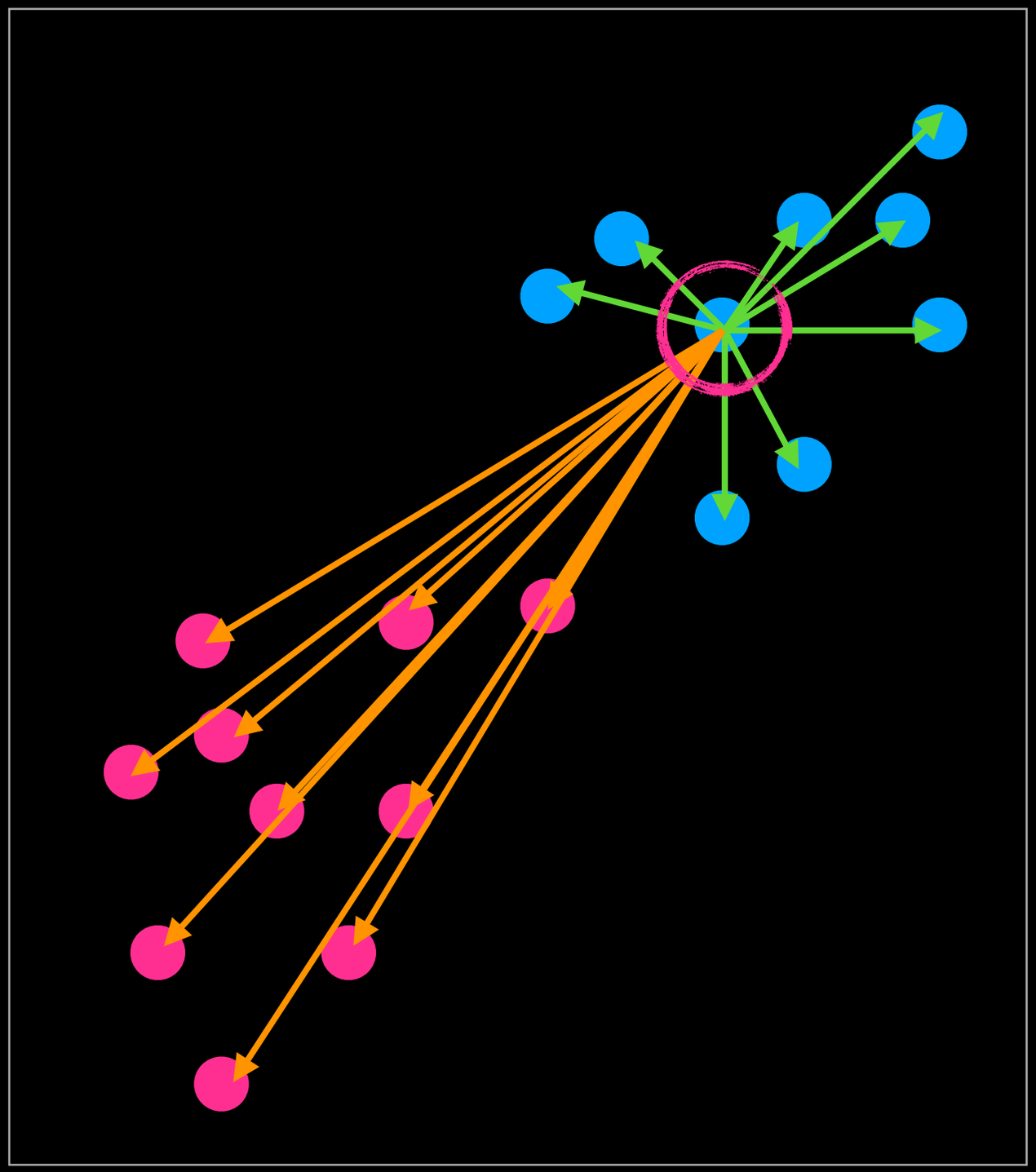
How Many Clusters?

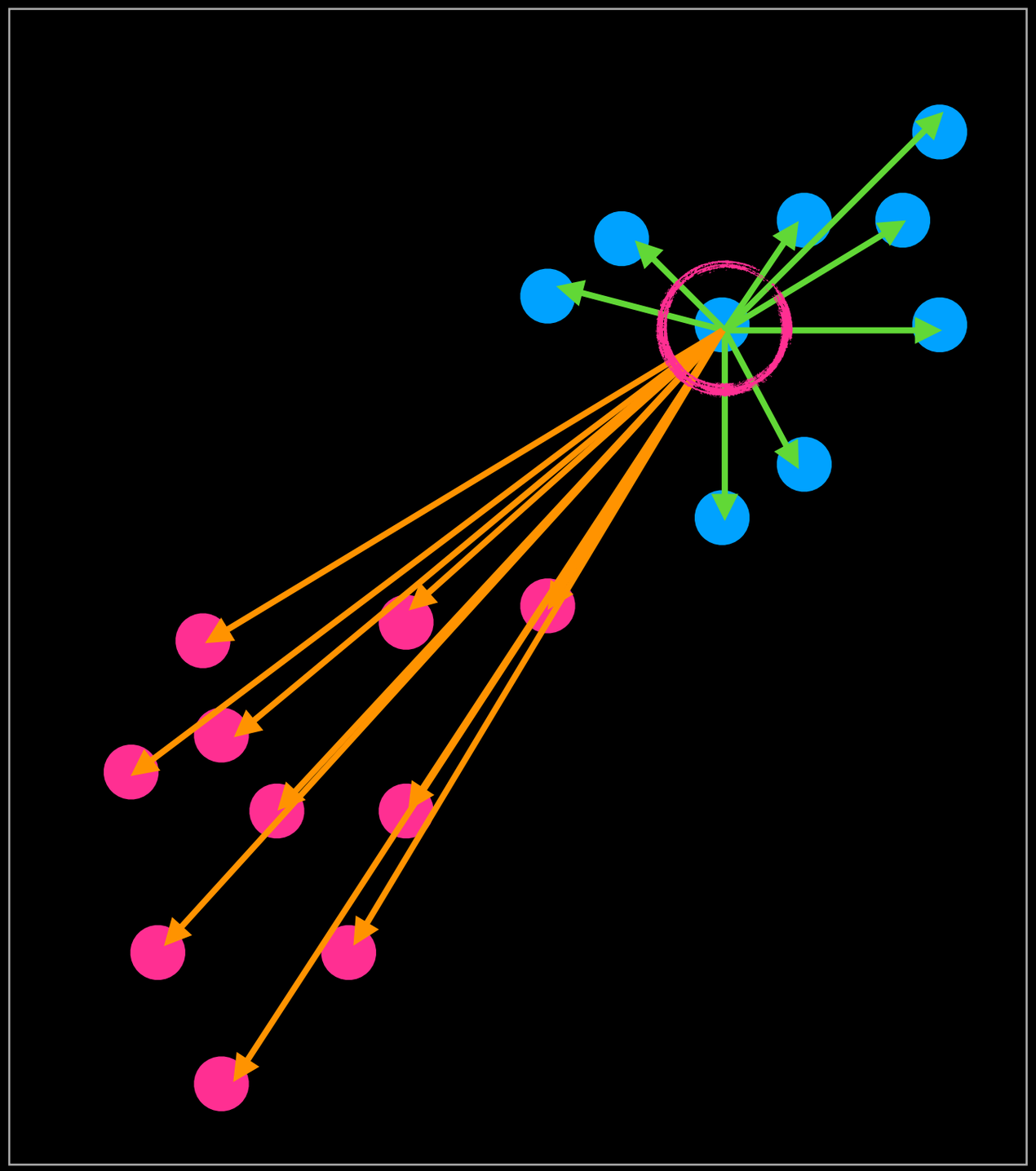


Silhouette Score

a = *mean intra-cluster distance*

b = *mean dist. nearest cluster*

How Many Clusters?



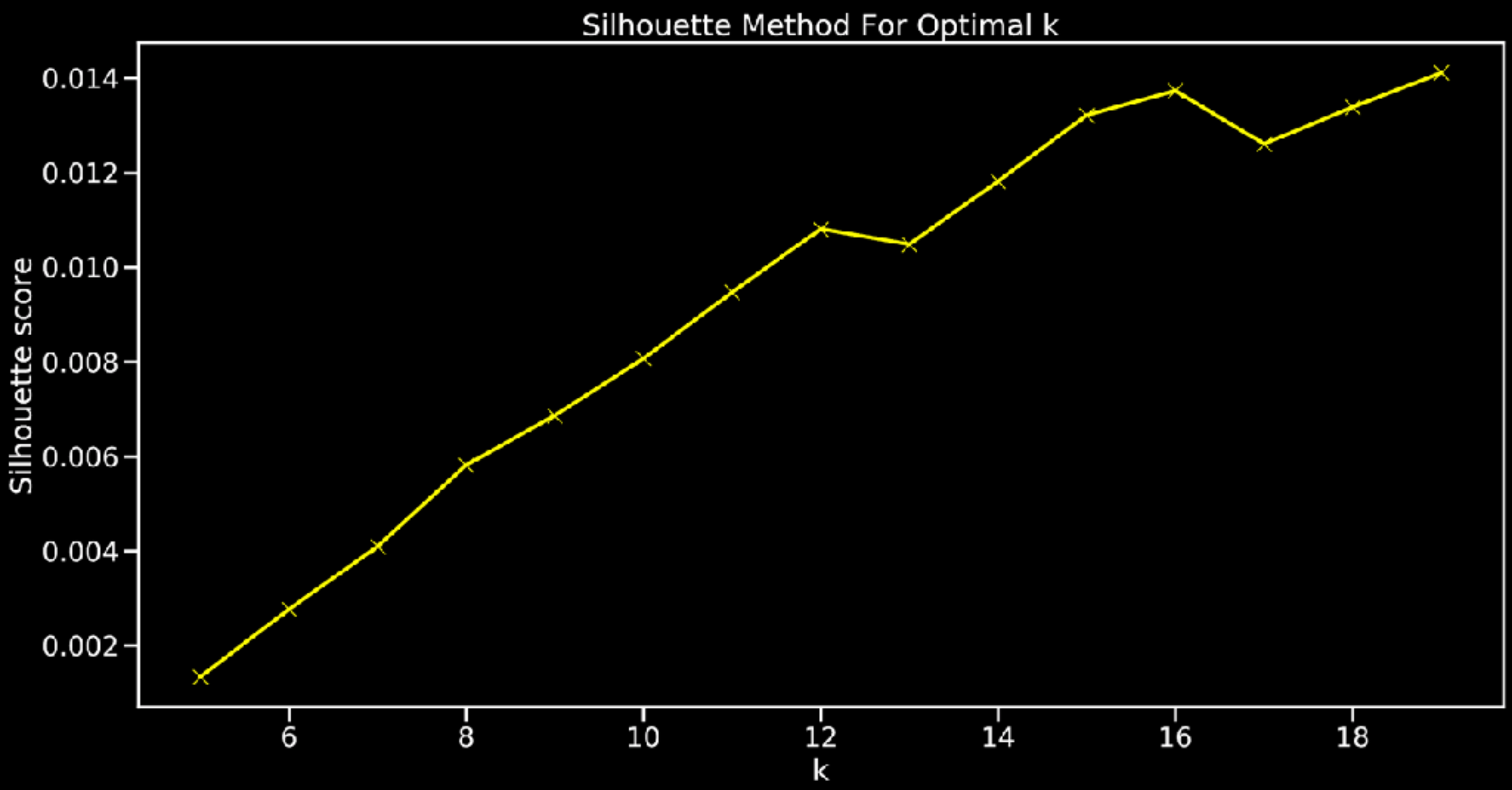
Silhouette Score

a = mean intra-cluster distance

$$S = \frac{(b - a)}{max(a, b)}$$

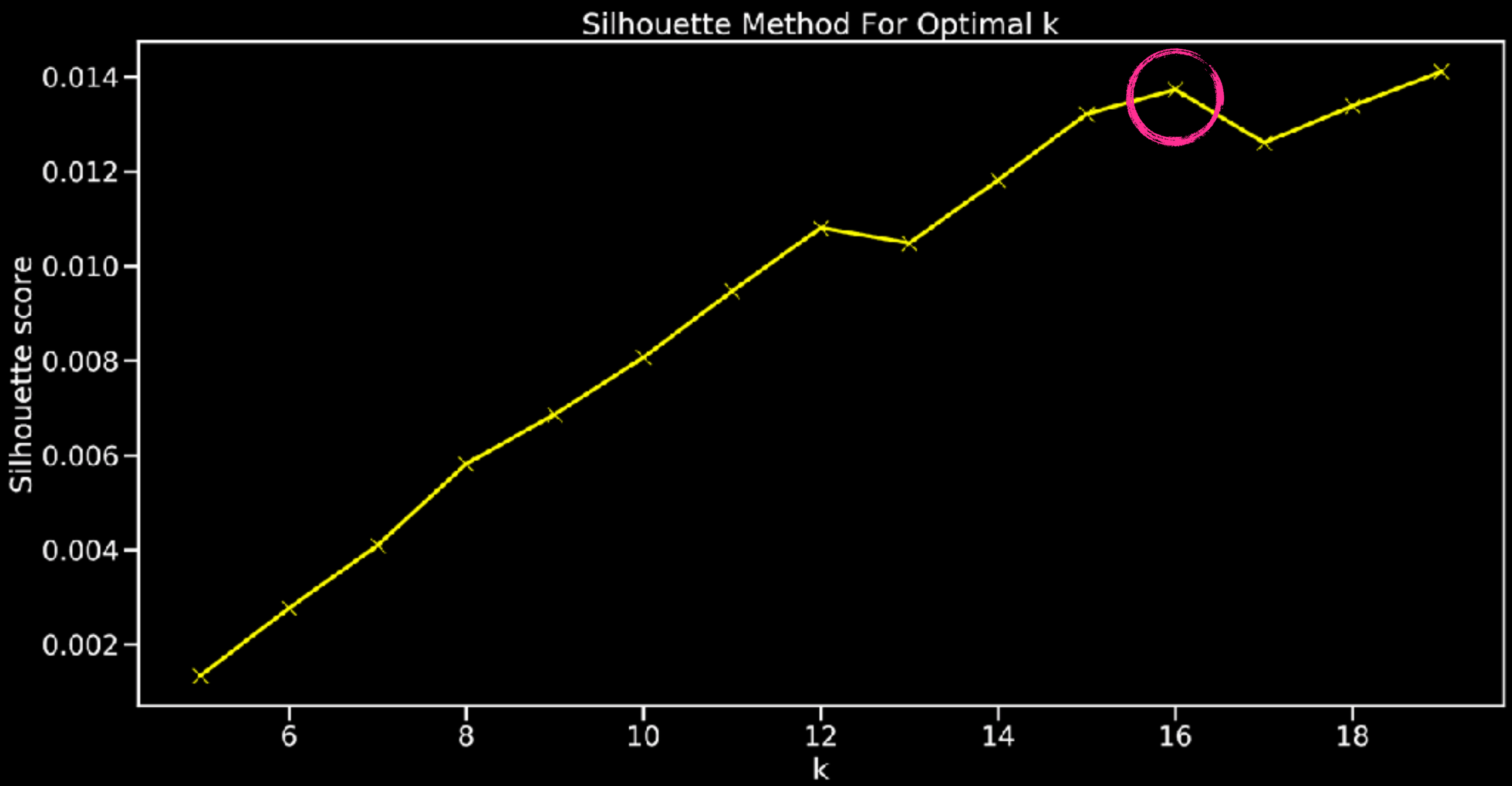
b = mean dist. nearest cluster

Silhouette Scores



Bocconi

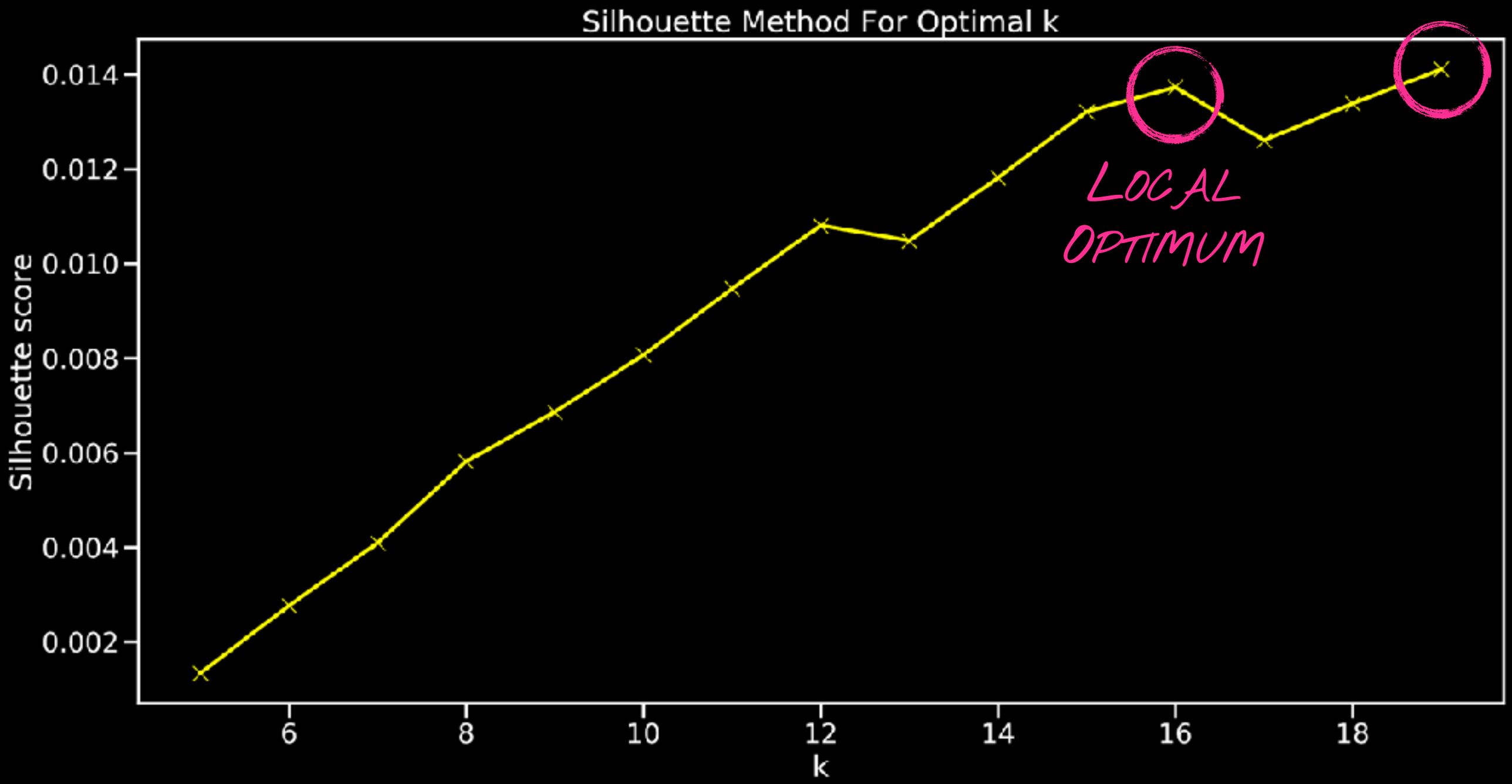
Silhouette Scores



Bocconi

Silhouette Scores

DEPENDS ON PATIENCE|COMPUTE POWER



Bocconi

Supervised Evaluation Metrics

Homogeneity

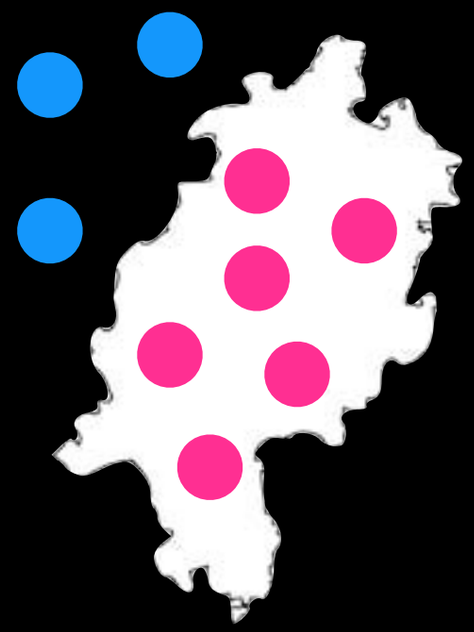
cluster has only 1 gold label

Supervised Evaluation Metrics

Homogeneity

cluster has only 1 gold label

Good:



Supervised Evaluation Metrics

Homogeneity

cluster has only 1 gold label

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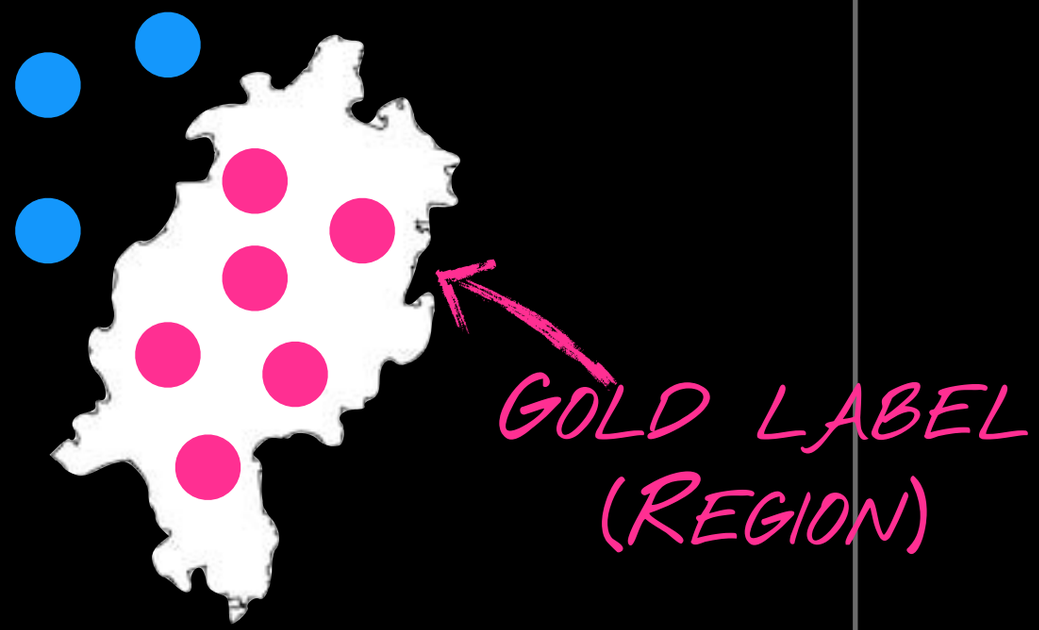

Bocconi

Supervised Evaluation Metrics

Homogeneity

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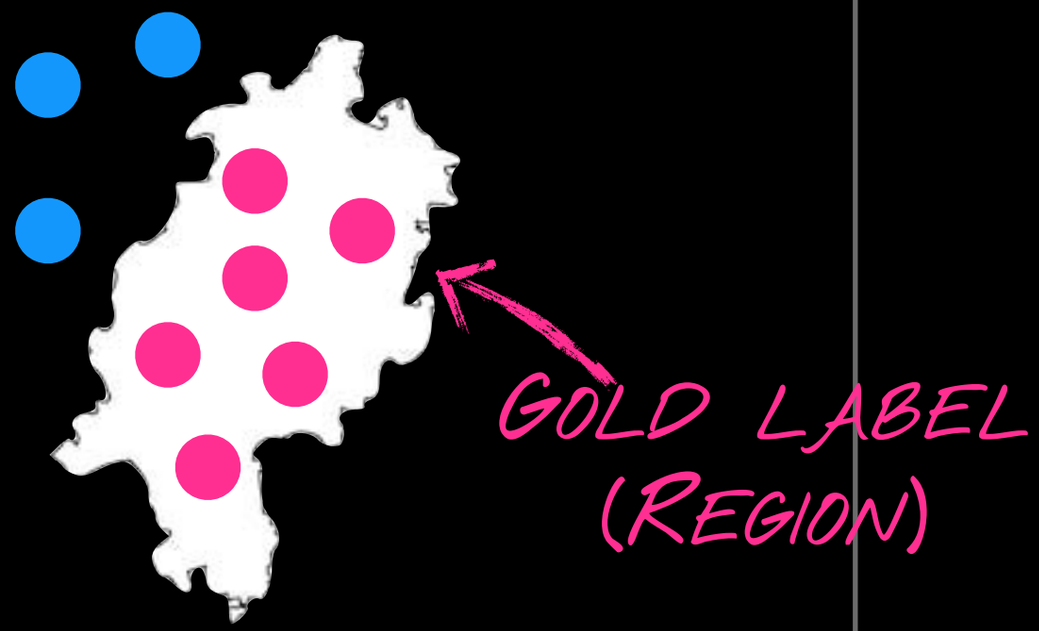
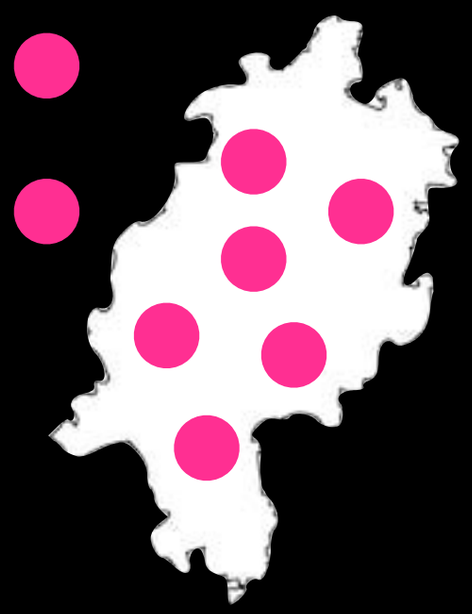


Bad:

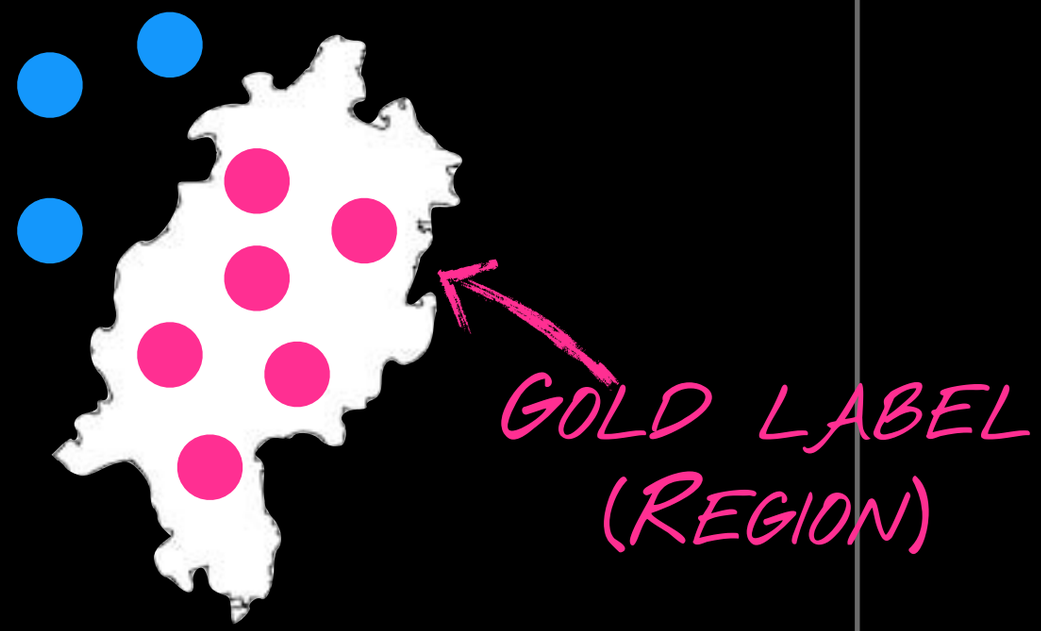


Supervised Evaluation Metrics

Homogeneity

cluster has only 1 gold label

Good:



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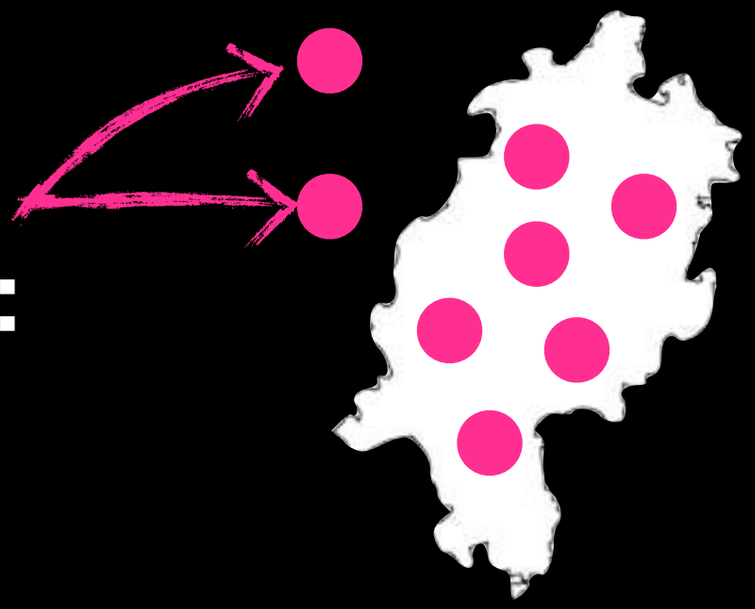
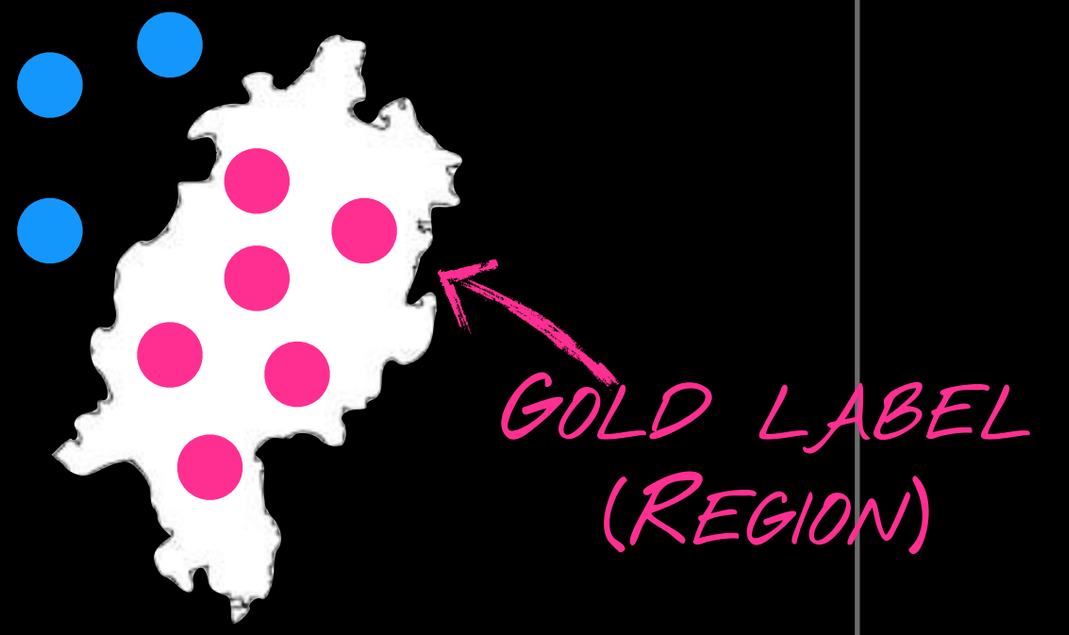
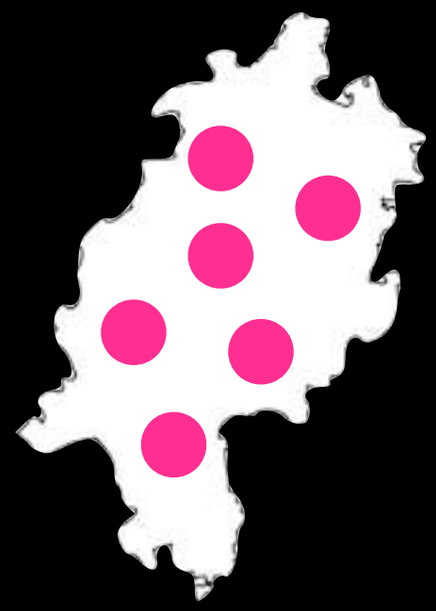
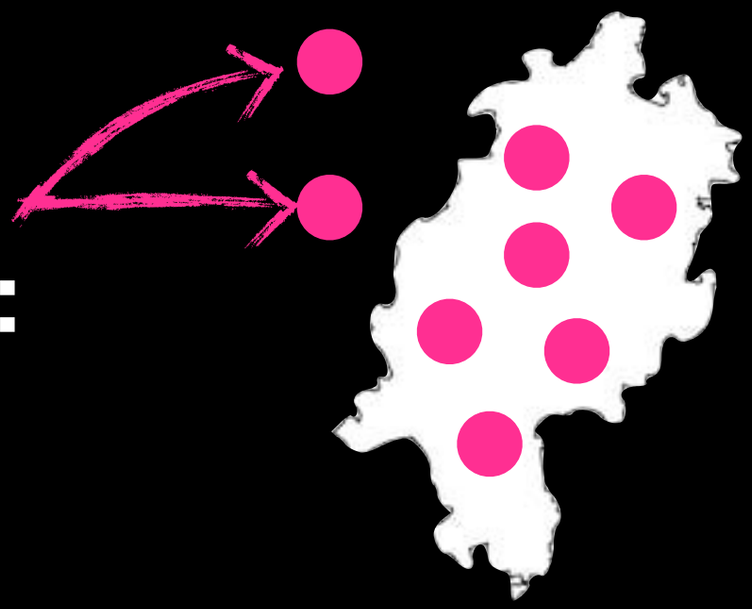
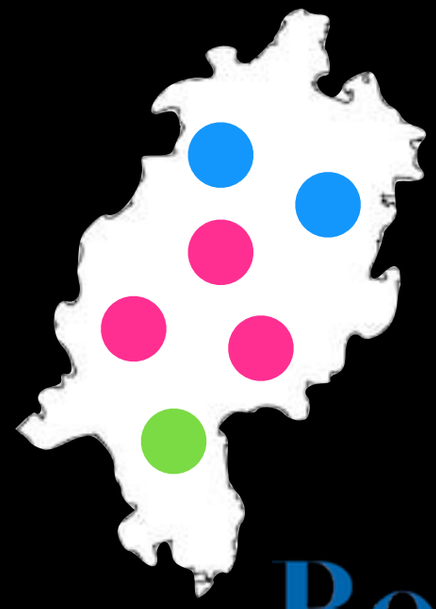


Supervised Evaluation Metrics

	Homogeneity *cluster* has only 1 gold label	**Completeness** *gold label* has only 1 cluster
Good:		
Bad:		

Comparison

	***k*-means**	**Agg**
scalable	yes	no (up to ~20k)
repeatable result	no	yes
include external info	no	yes
Good on dense clusters?	no	yes

Wrapping Up

Bocconi

When to Use What

	Discrete Features	Embeddings
Latent topics	NMF	*Not applicable*
RGB translation	NMF	SVD + scaling
Plotting	SVD	t-SNE
Clustering	*Reduce dimensions*	*Use as-is*

Take-Home Points

- **Matrix factorization** assumes latent concept dimensions
  - Can be used for semantic similarity (**LSA**)
  - Reduced components can be **visualized** in **graphs** or as **RGB** colors
- **Clusters** can group input in new ways
- Trade-off between speed and interpretability