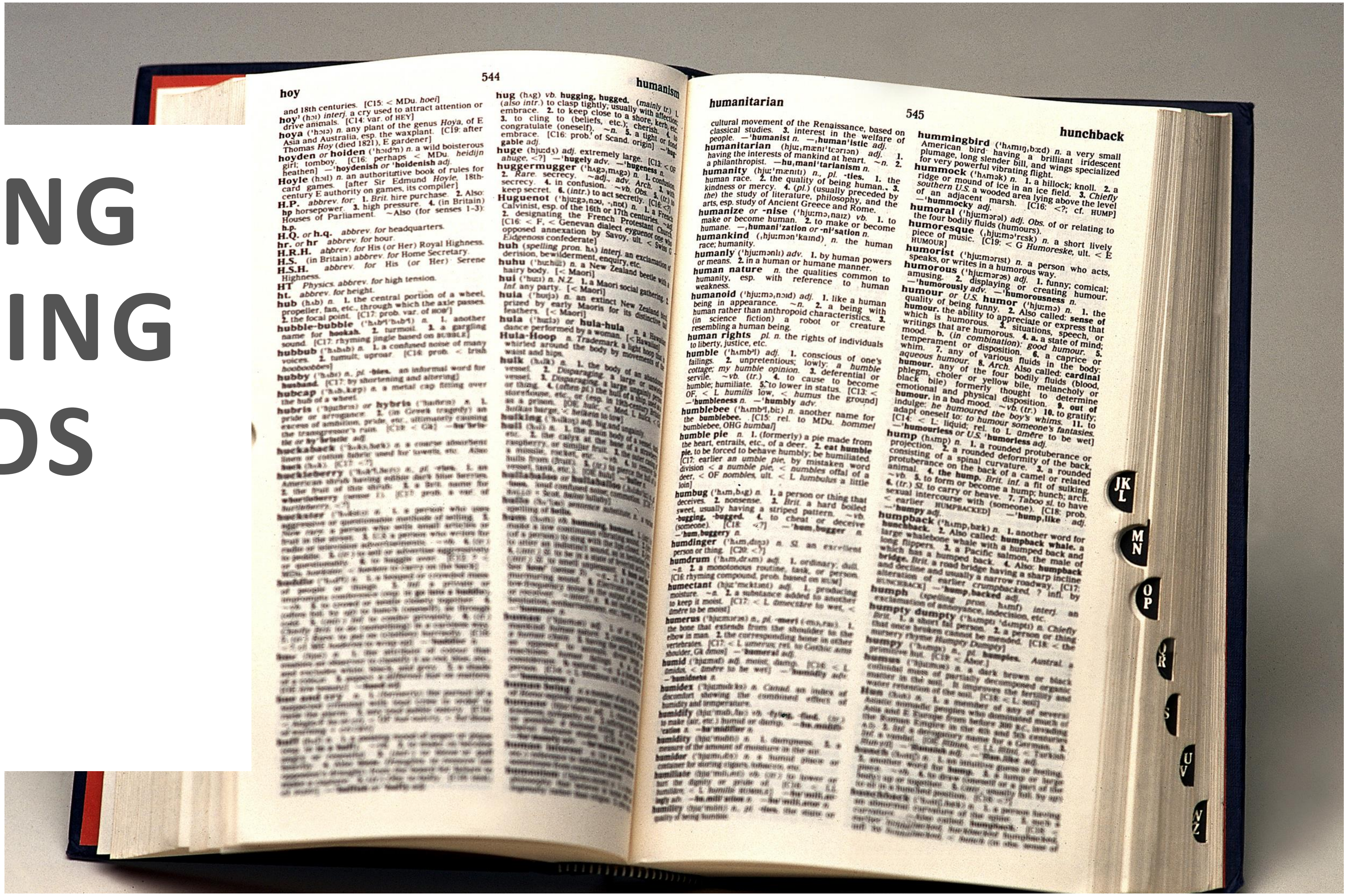
VISUALIZING THE MEANING OF WORDS

William Fisher



My research is on episodic memory (fascinating!)
My lab uses stories and narratives to investigate phenomena
Lab mates do research on spontaneous thought

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We get lots of text data

I’m going to share some *cool* ways of visualizing verbal meaning

Goals of my presentation

I hope to communicate how the following methods
can help **visualize the human experience in free-thinking or recall tasks** and
visualize neat features of narratives

Until recently, quantifying and visualizing the meaning of words was very challenging and laborious

Natural Language Processing (NLP) provides <u>many</u> useful tools to efficiently quantify the meaning of text

NLP

- The semantic meaning of texts and how similar they may be to each other
- Emotionality
- Sentiment (positive or negative)
- Topics or themes that are present throughout a text

NLP

- Word2Vec (Mikolov et al., 2013)
- GLoVe; Global Vectors of Word Representation (Pennington et al., 2014)
- VADER; Valence Aware Dictionary and sEntiment Reasoner (Hutto & Gilbert, 2014)
- USE; Universal Sentence Encoder (Google; Cer et al., 2018)
- STM; Structural Topic Modelling (Roberts et al., 2019)
- BERT; Bidirectional Encoder Representation from Transformer (Google)
- GPT; Generative Pretrained Transformer (OpenAI)

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GLoVe Word Embeddings

- Pretrained on Wikipedia text
- Semantic meaning determined by word co-occurrence
- Each word is represented by a 300-dimension vector
- Words that are similar to each other exist closer together in this 300-dimension semantic space

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What does this look like to us?

GLoVe Word Embeddings

Dimension	Apple	Orange	Yellow
Dim1	0.046560	0.213180	-0.007436
Dim2	-0.255390	-0.257230	0.131690
….	….	….	….
Dim300	-0.125590	0.013630	0.103060

Cosine similarity in R to determine semantic similarity

Word 1	**Word 2**	**Cosine Similarity**
Apple	Orange	
Orange	Yellow	
Yellow	Apple	

Cosine similarity in R to determine semantic similarity

Word 1	Word 2	Cosine Similarity
Apple	Orange	0.42
Orange	Yellow	0.59
Yellow	Apple	0.19

How can we use this tool to visualize the meaning of these words?

Free Thinking or Free Recall Word Chain

Apple

Orange

Strawberry

Fruit

Vegetable

Farm

Tractor

Soil

Earth

Mars

Space

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Semantic clusters
(Kahana et al., 2022)

TYPICAL METHODS OF VISUALIZATION

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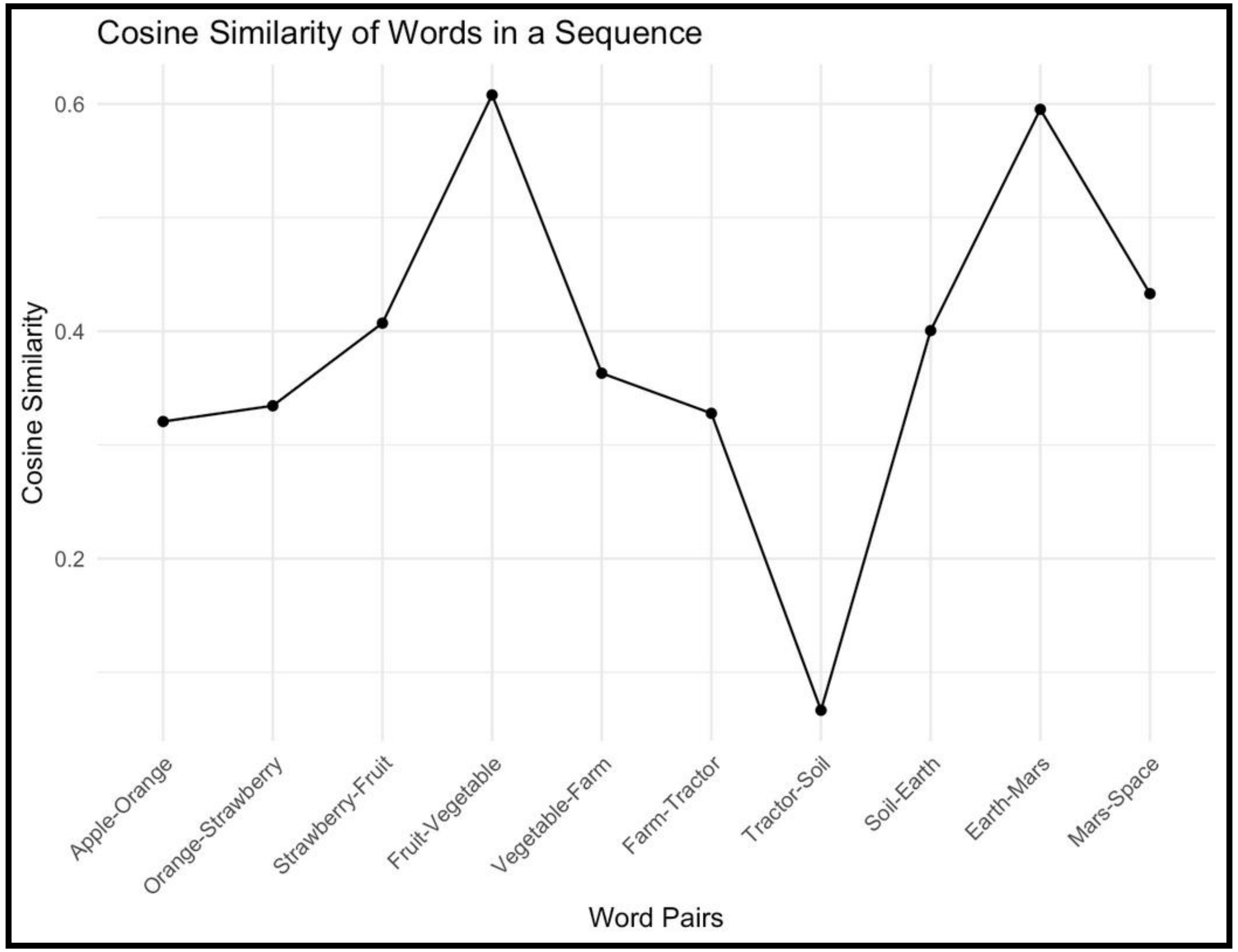
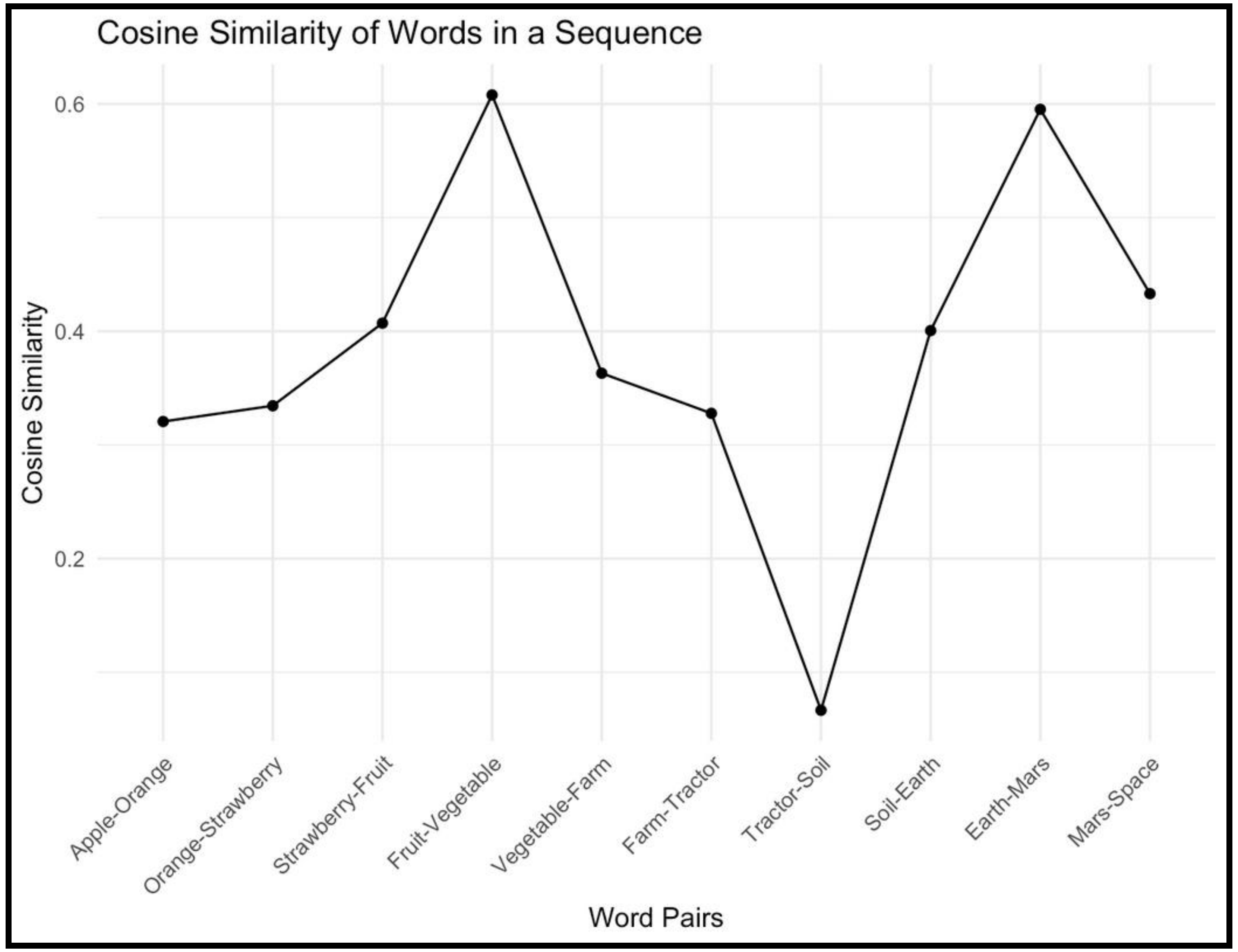
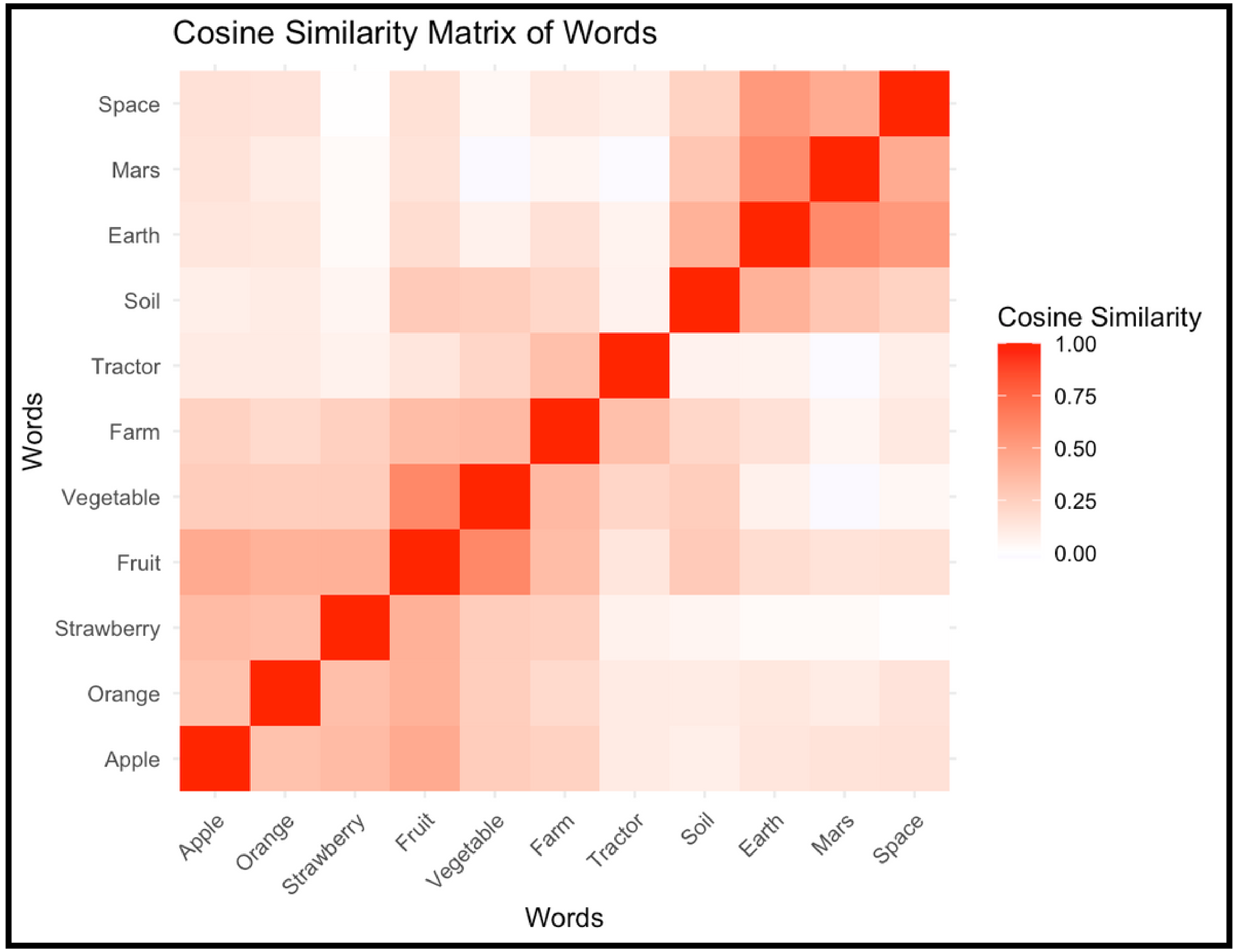


TYPICAL METHODS OF VISUALIZATION





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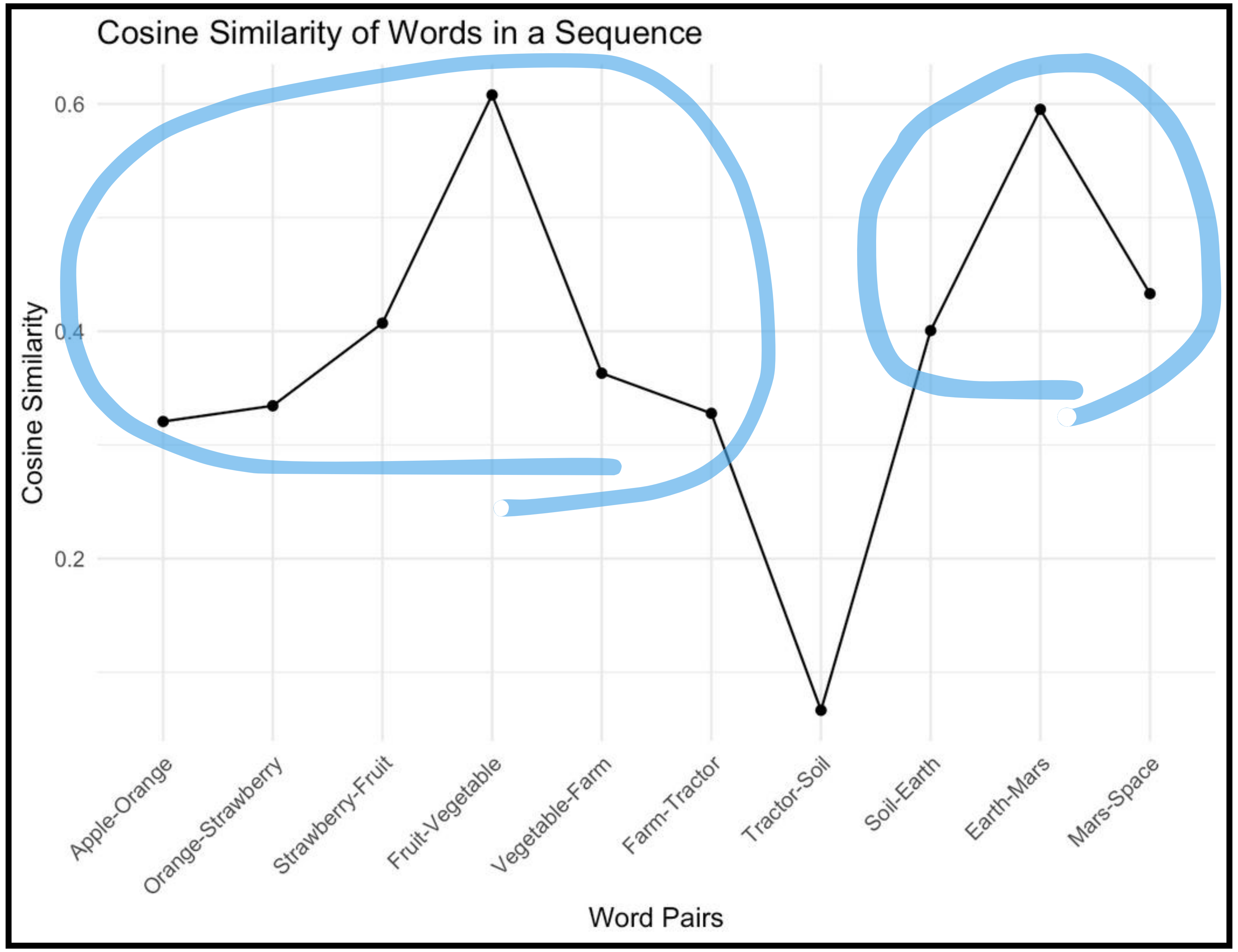

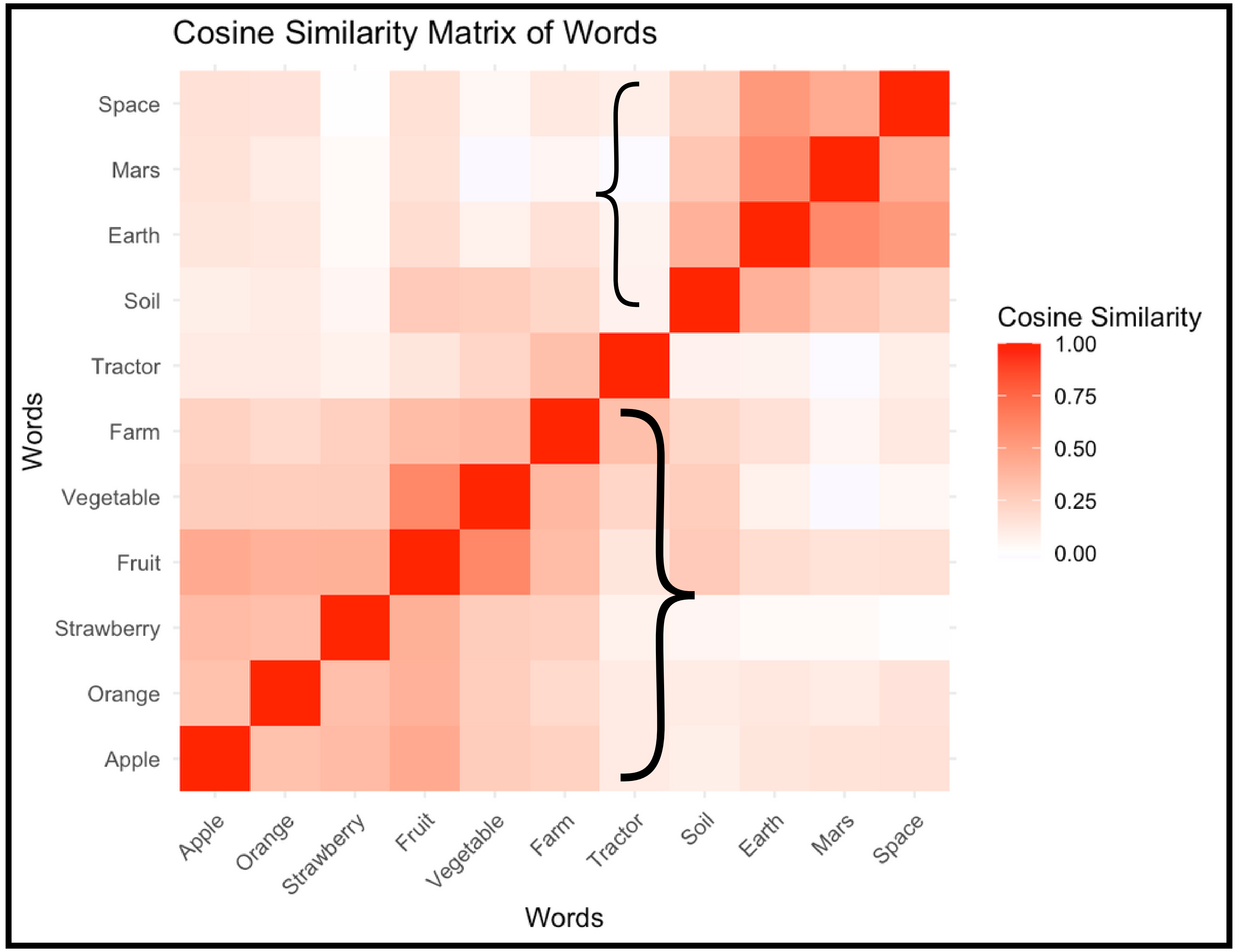

You can see semantic clusters

It would be neat if we could plot the “semantic space” that these words exist in

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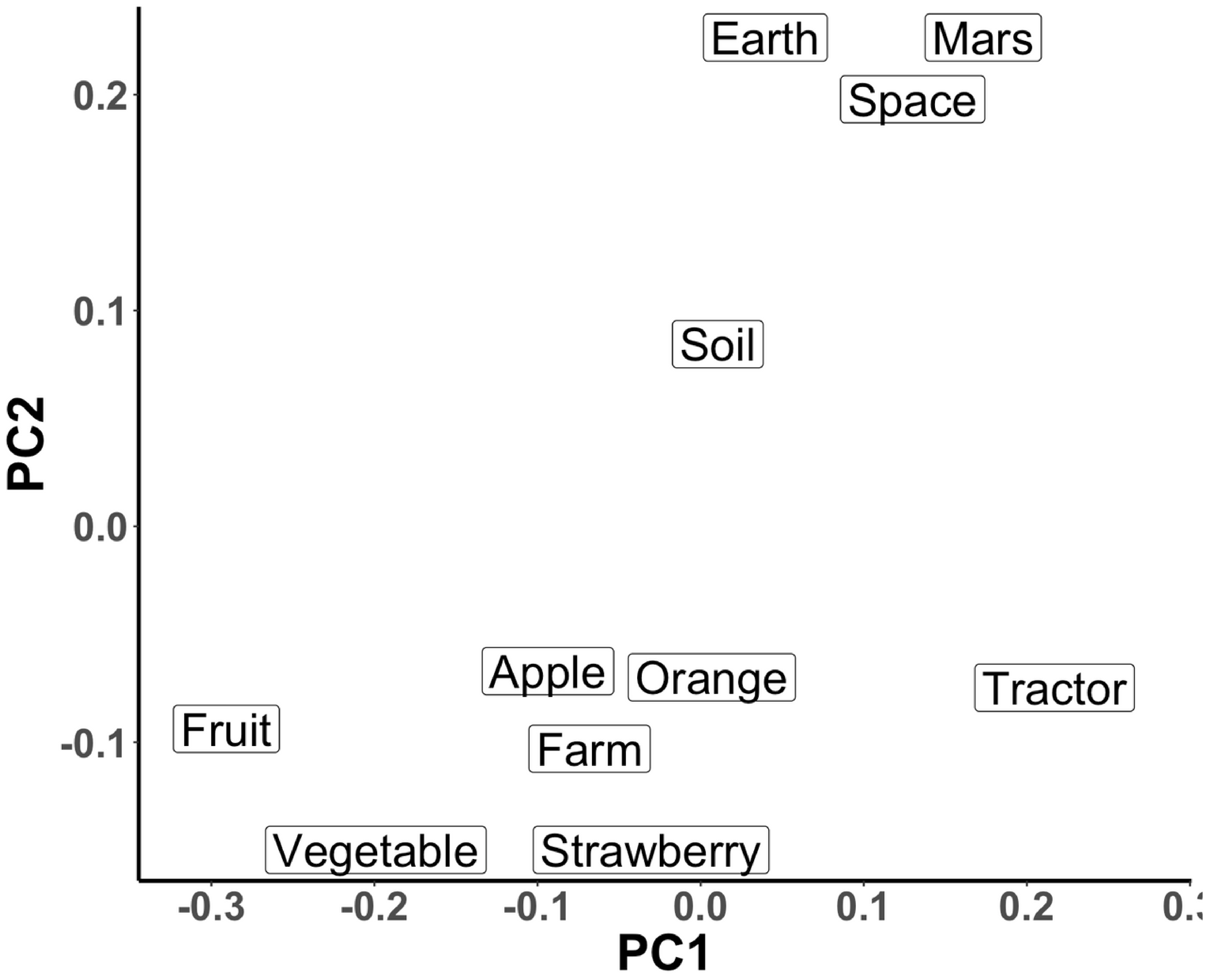
How can we visualize words that are represented by 300 dimensions?

PRINCIPAL COMPONENT ANALYSIS TO MEANINGFULLY REDUCE THE DIMENSIONS

Dimen-sion	Apple	Orange	Yellow
Dim1	0.0465	0.2131	-0.007
Dim2	-0.255	-0.257	0.1316
….	….	….	….
Dim300	-0.125	0.0136	0.1030

Word	Dim1	Dim2
Apple	0.2943	-0.9231
Orange	0.0204	0.4528
Yellow	-0.1121	0.3121

2D VISUALIZATION OF WORD CHAIN USING PCA



2D ANIMATION OF WORD CHAIN

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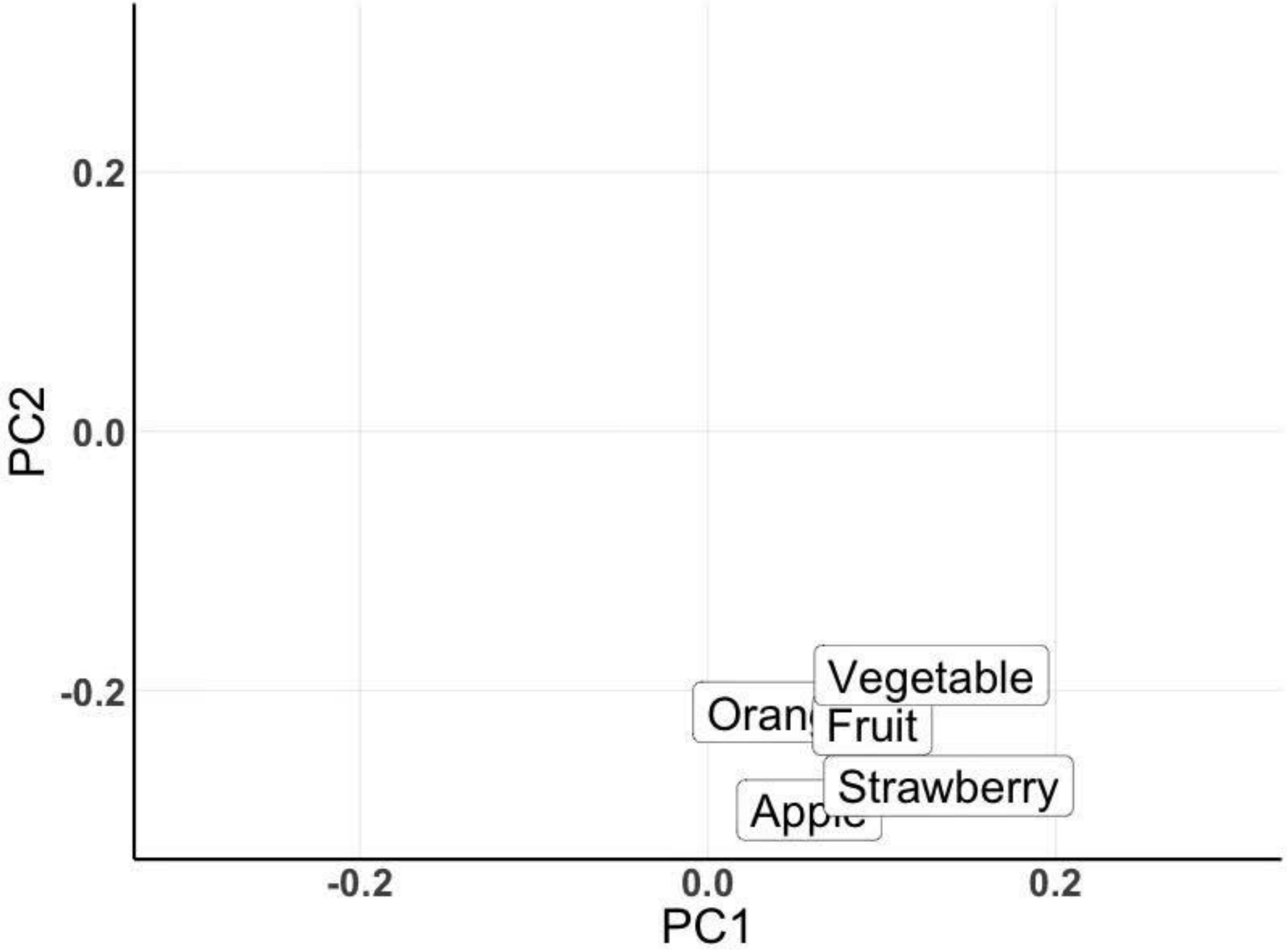

Story themes linger in mind after engaging with a story.
(Bellana et al., 2022)

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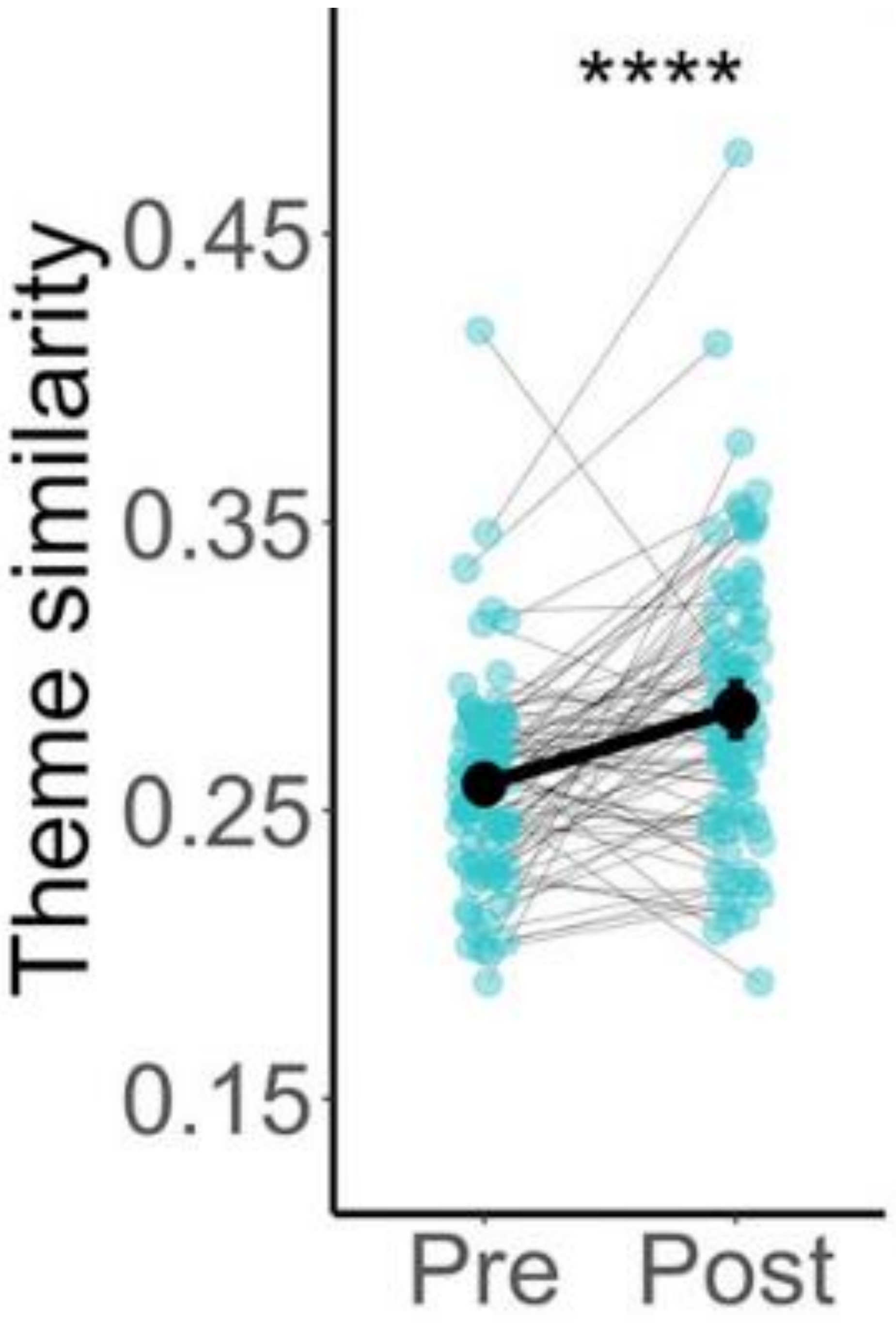
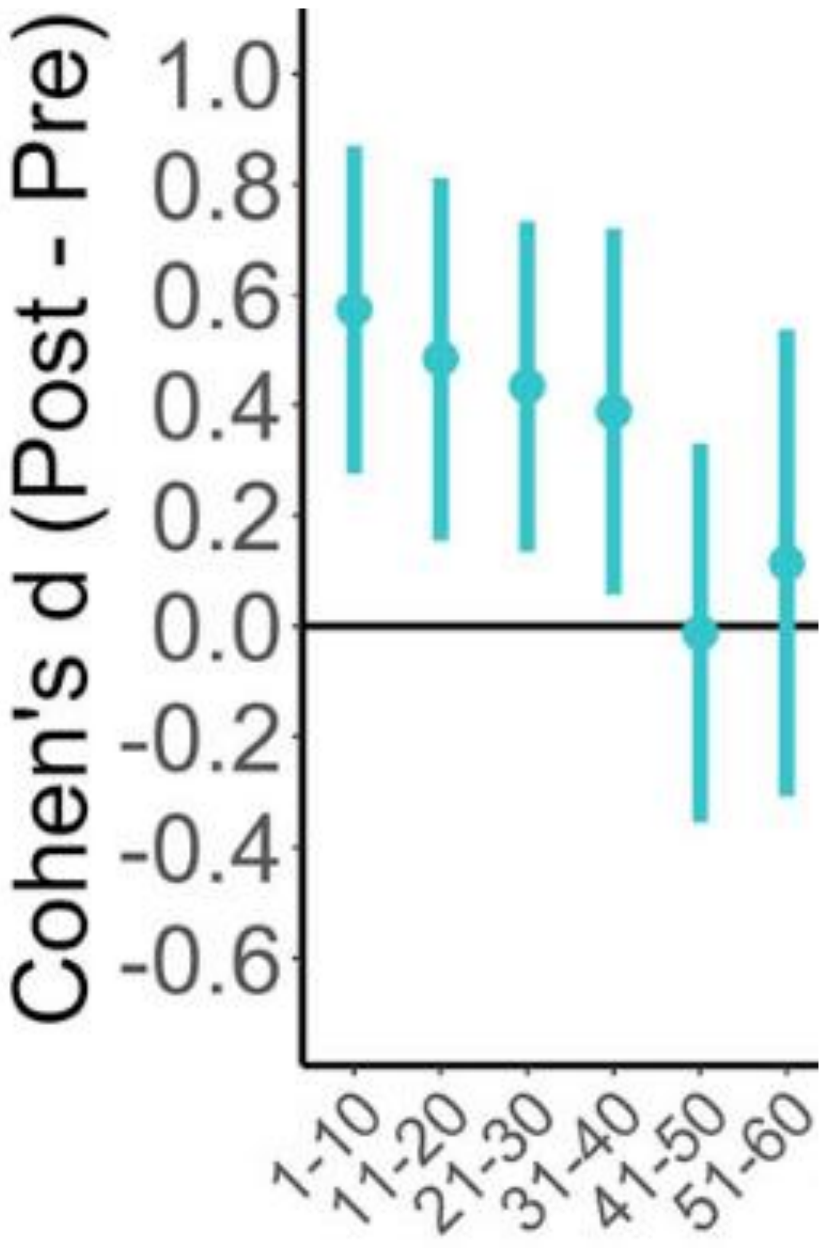
HOW CAN WE VISUALIZE THIS?

Method 1 - static





Windowed Free Associates

(Bellana et al., 2022)

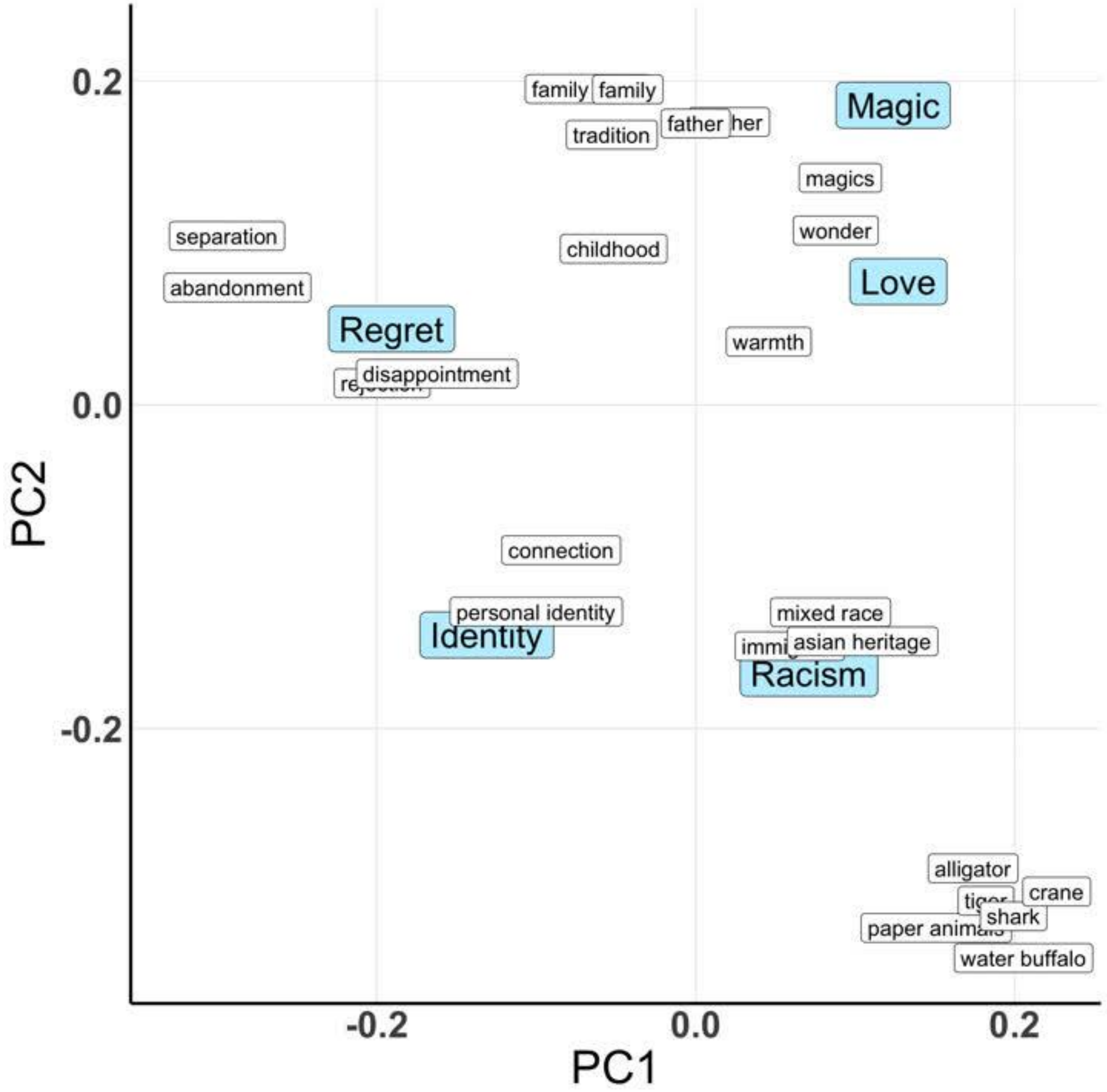
Method 2 - dynamic

Method 2 - dynamic

Steps:

1. **Structural Topic Modelling** to extract story themes
2. PCA on word embeddings for story themes
3. PCA on word embeddings for post story free association chains
4. Plot animation with Dim1 on x-axis and Dim2 on y-axis

Method 2 - dynamic



GPT generated word chain so it lacks the temporal semantic clustering

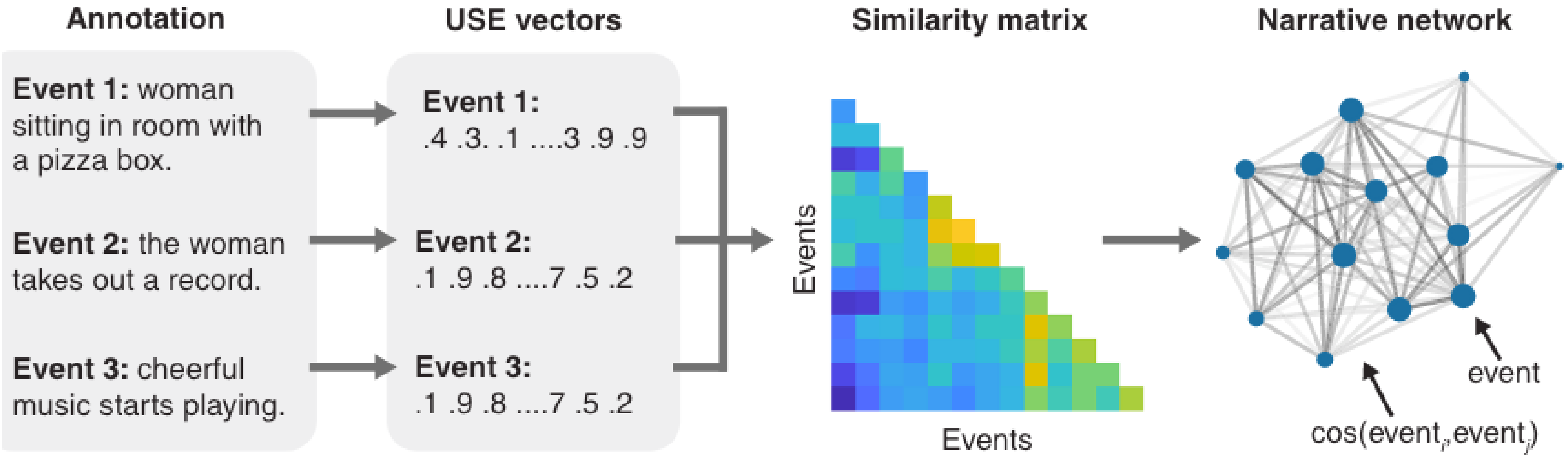
VISUALIZING STORIES

Story events

Universal Sentence Encoder

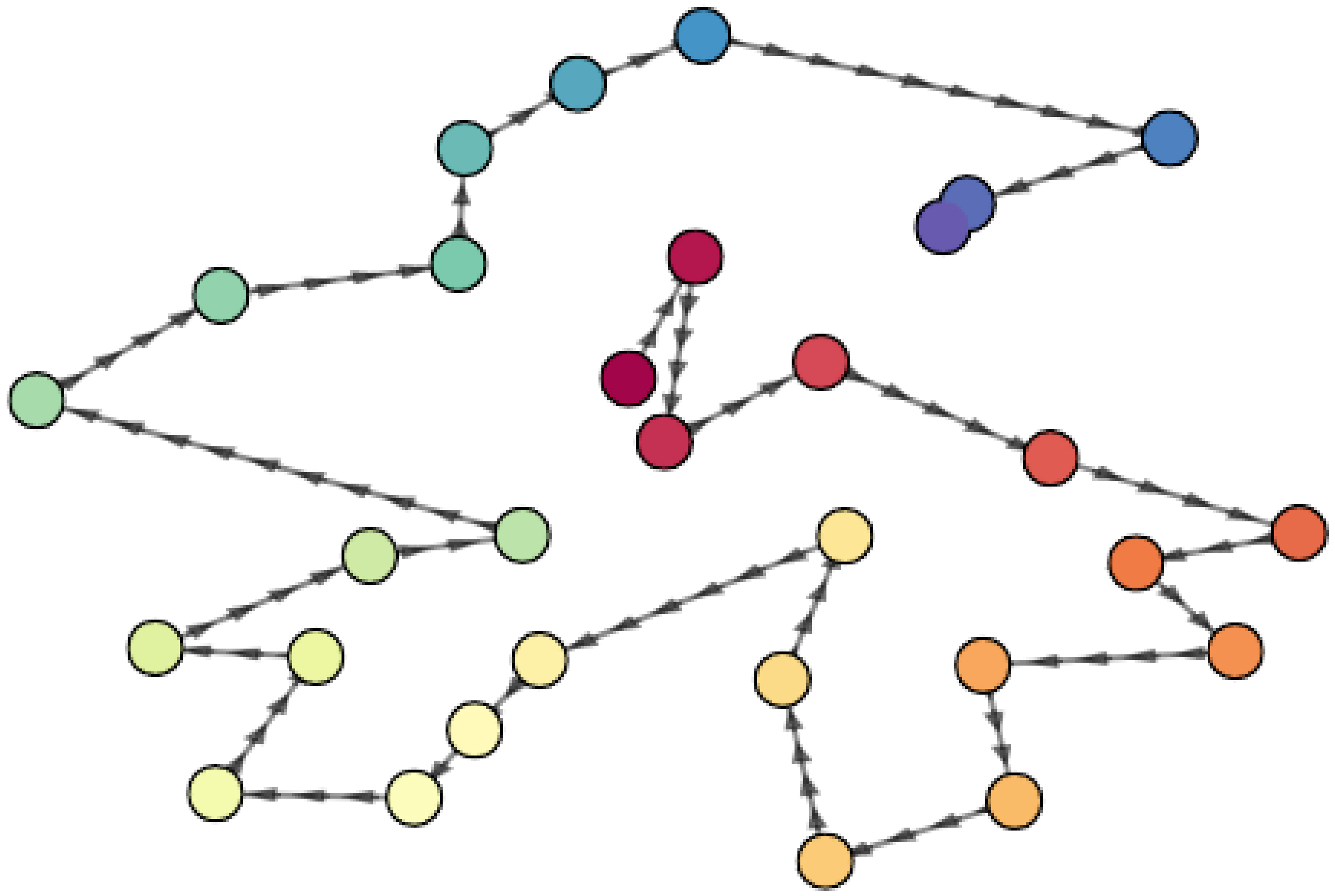
Cosine similarity

Network graph of story event interrelatedness



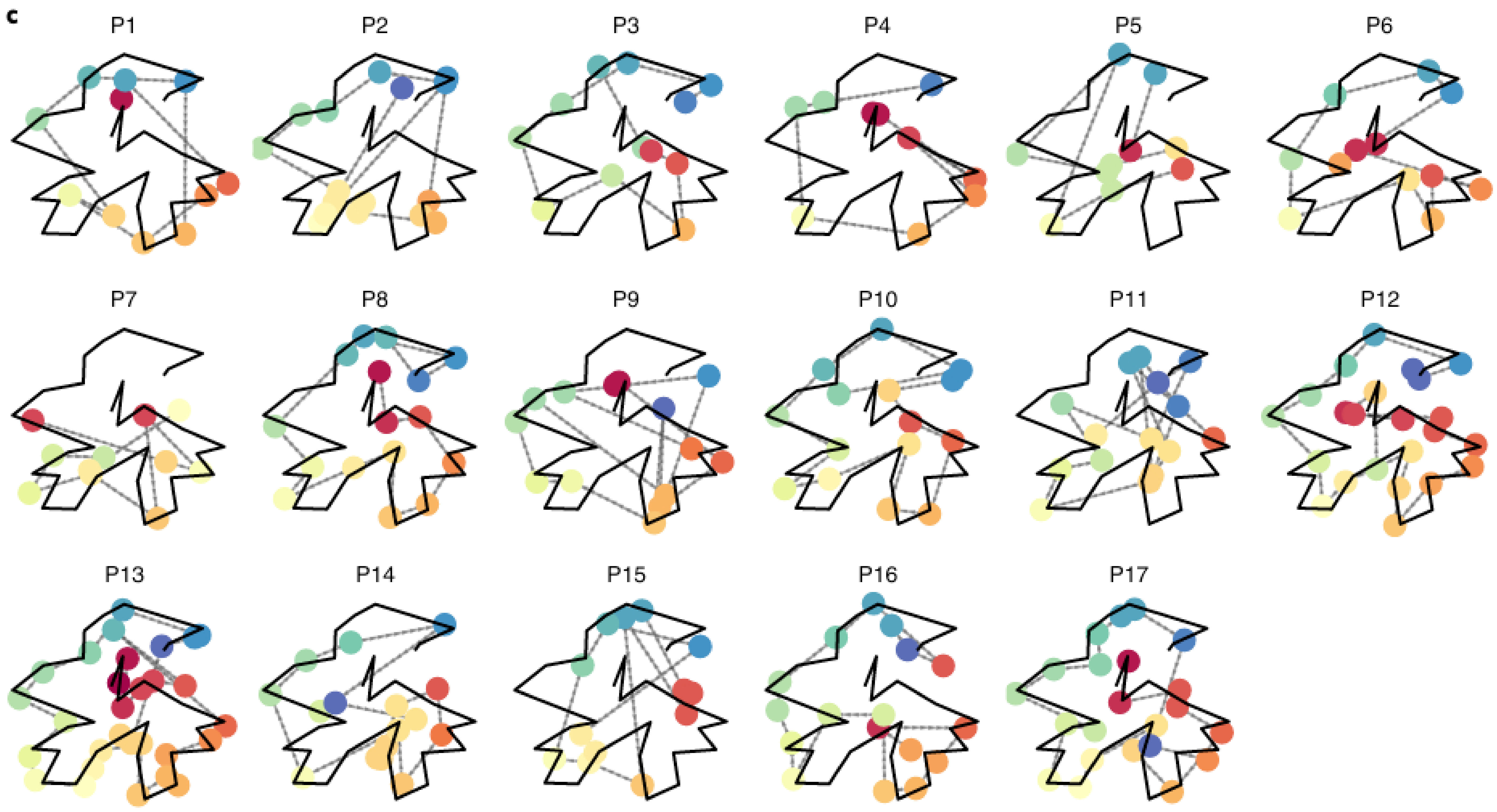
(Lee & Chen, 2022)

HOW ABOUT THE UNFOLDING OF A STORY?



Early story events are in red and later events in blue

(Heusser et al., 2021)



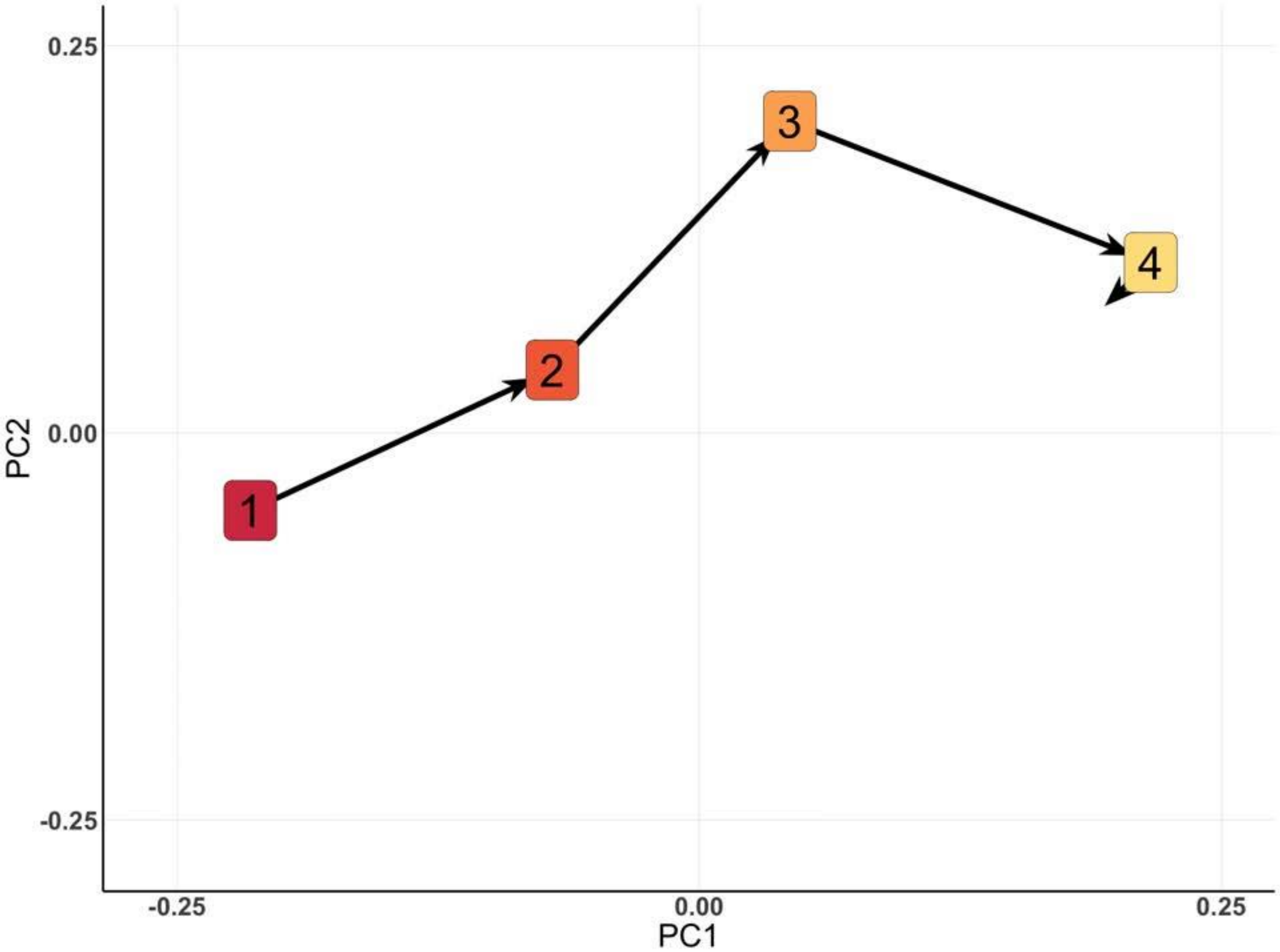
Visualizing how participant recall semantic trajectory (coloured) aligns with the story's narrative arc (black line) (Heusser et al., 2021)

VISUALIZING THE SEMANTIC PATH OF A STORY

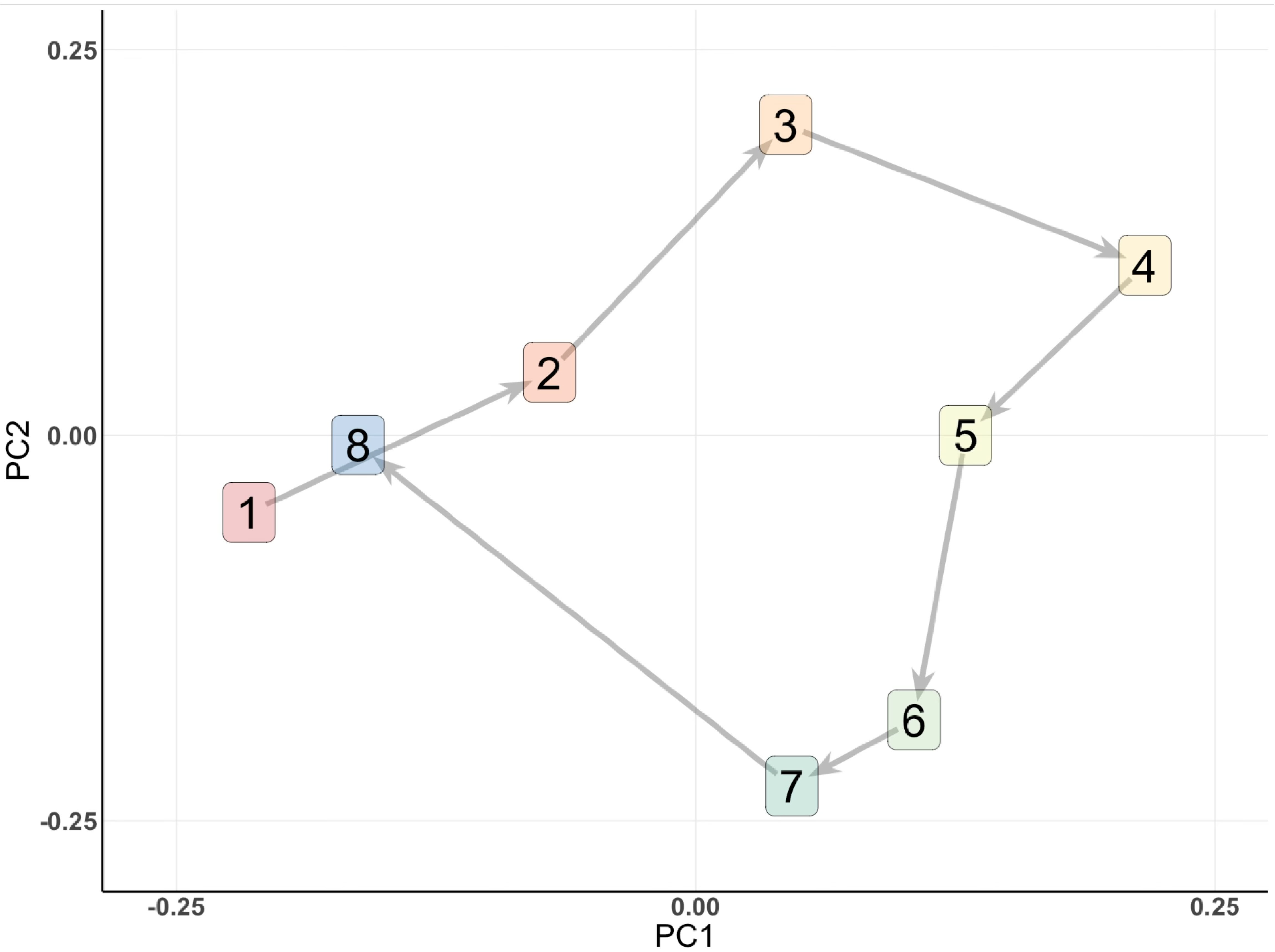
Steps:

1. Identify event boundaries in a story
2. **USE** on each story event
3. PCA on USE embeddings
4. Plot animation with Dim1 on x-axis and Dim2 on y-axis

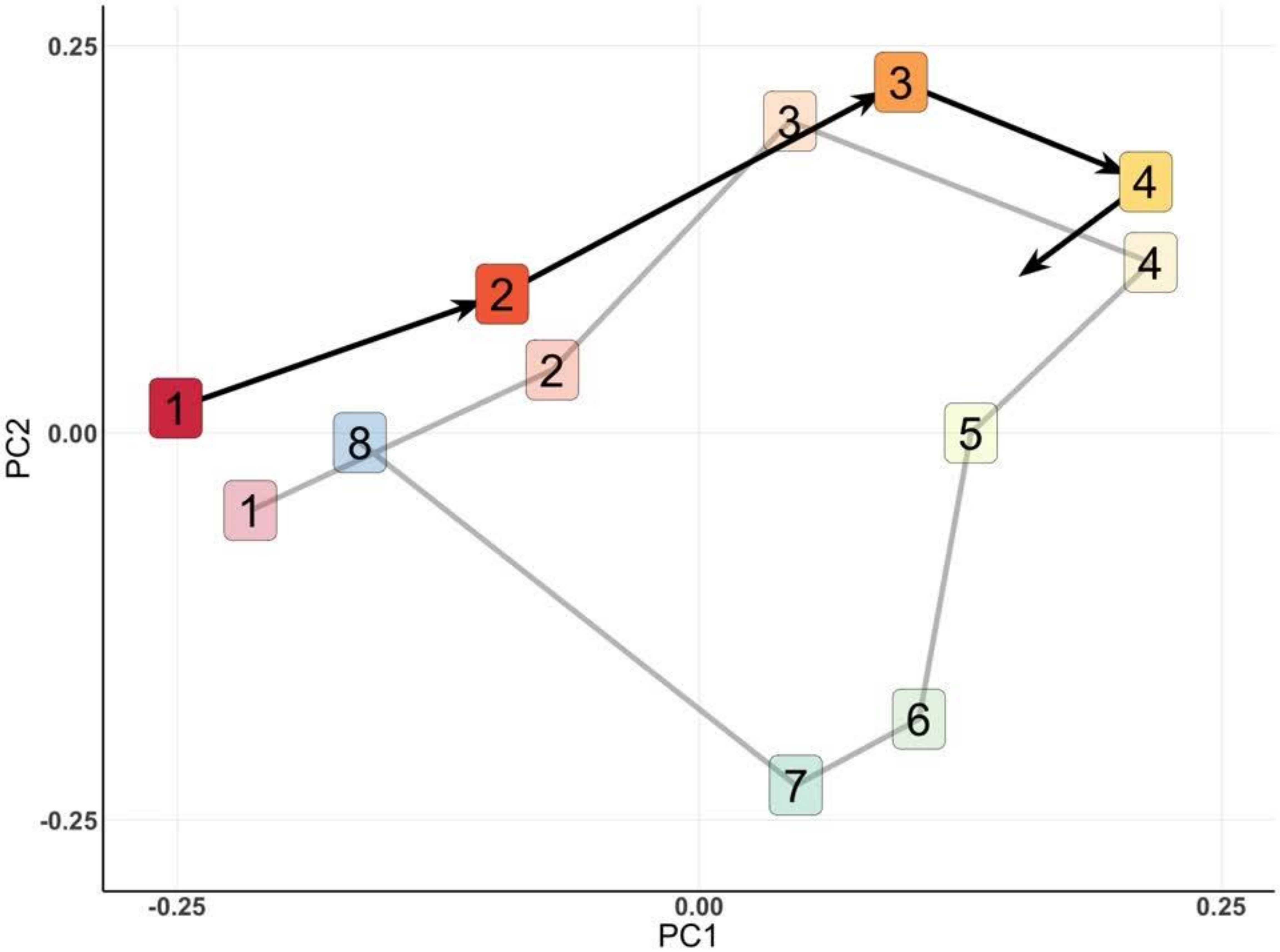
VISUALIZING THE SEMANTIC PATH OF A STORY



VISUALIZING THE SEMANTIC PATH OF A MEMORY OF A STORY



VISUALIZING THE SEMANTIC PATH OF A MEMORY OF A STORY



THANKS FOR LISTENING!

References

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