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LEARNING MULTIMODAL REPRESENTATION FROM COMPLEX DATA FOR FAULT DIAGNOSIS

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1 CONTEXT

- Large monitoring datasets underexploited for predictive maintenance
- Continuous stream analysis
- Heterogeneous and complex data
- Predict fault and plan maintenance operations

2 CHALLENGES/OBJECTIVES/GAPS

- Heterogeneous data management:
  - Structured / non-structured
  - Continuous / sparse and discrete
  - Different time scales
- Weakly supervised data
- Online setting

→ How to handle these pieces of knowledge?
  - Fuse complementary parts
  - Discard redundancy / irrelevant parts

→ How to deal with missing / imbalanced modalities?

→ How to integrate reliability levels?

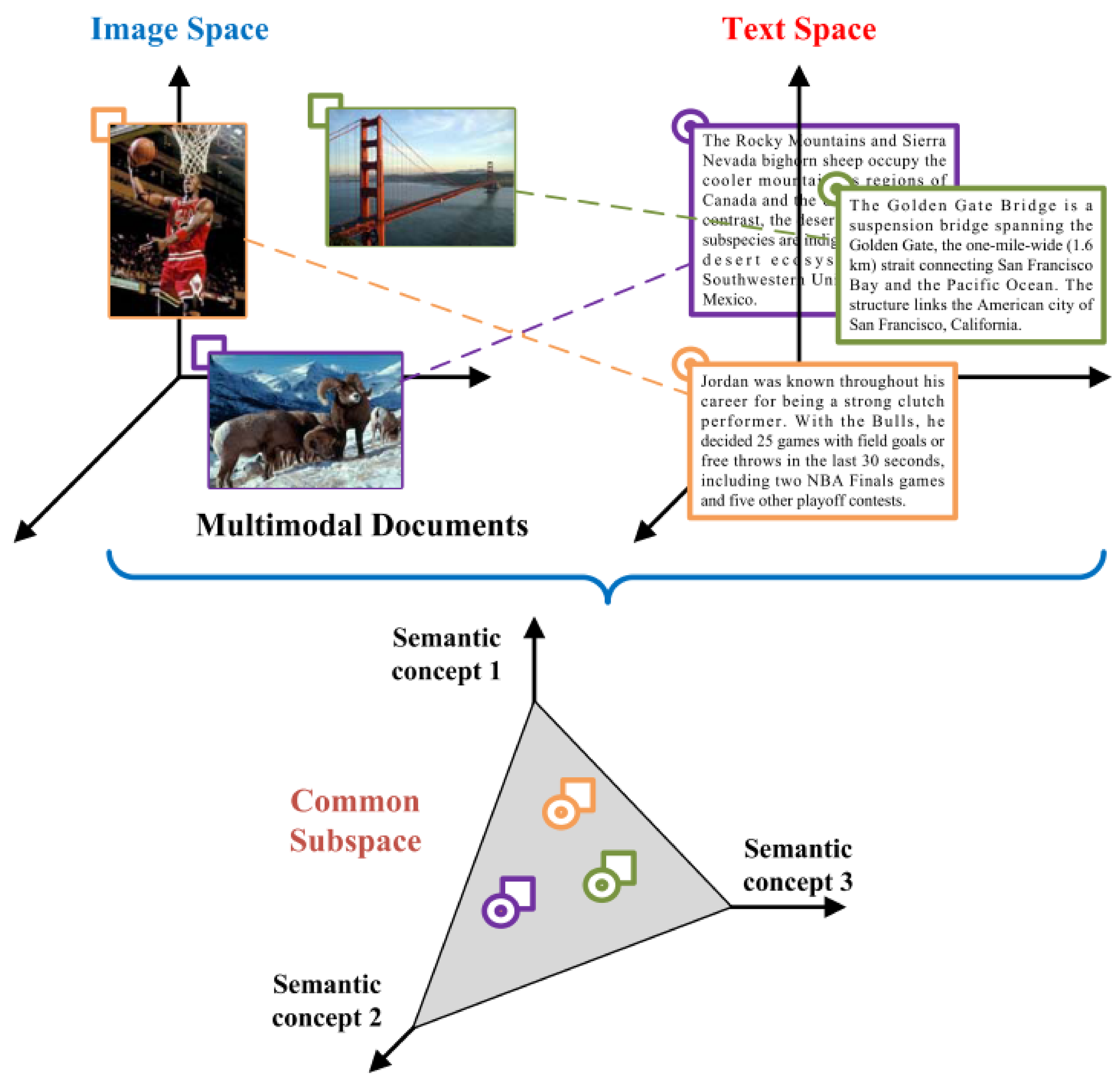

Figure 1: Common subspace learning, where multimodal data with similar semantics are represented by similar vectors [1]

3 RESEARCH METHOD

$\left.\begin{array}{l}\text{Unsupervised setting}\\ \text{Not task-guided}\\ \text{Able to generate missing data}\end{array}\right\}$ Generative model

Learning a joint multimodal representation in a latent subspace.

$$z = f(x_1, x_2, \ldots, x_m)$$

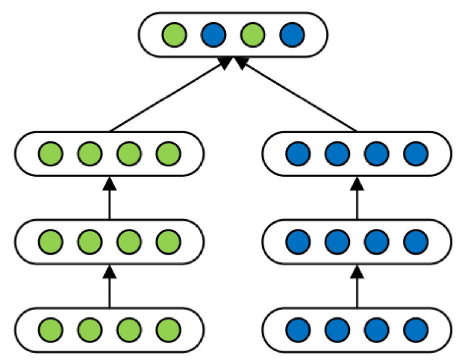

Figure 2: Deep joint representation aims to learn a shared semantic subspace [1]

Viable architectures:

- PGM [5]
- Multimodal AE [3]
- GAN [4], etc.

- Mimic human mecanism for information fusion: attention mechanism [2] / neuroscience

4 EXPECTED CASE STUDY

A typical setting would involve a system containing:

- Sensors time series
- Textual data from previous maintenances / diagnoses
- Structured description data
- Pictures, sound, etc.

→ Perform diagnosis: fault detection and isolation

Any system with multimodal data enabling to perform pathological cases detection

5 EXPECTED RESULTS

- Make substantial progress in the multimodal learning state-of-the-art
- Apply contributions to MPO project partner entities usecases

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