Embeddings

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Introduction

- Sparse versus dense representations; similarity; context
- Dimensionality reduction
- Word Embeddings
- Joint Embeddings

Problem statement

- Consider training a neural network on text
  - We need a vector representation of words
  - Obvious approach is One Hot Encoding into vectors of the same dimensionality as the vocabulary size
    - But, …
      - Very big vectors (>171k words in English vocab)
      - No notion of synonymy; all terms orthogonal

Problem statement

- We'd really like much lower dimensional vectors (far fewer weights)
- … this is a **dimensionality reduction problem**
- Ideally vectors should capture similarity (cat->kitten should be **closer** than cat->dog)
  - … we need to **learn similarity**

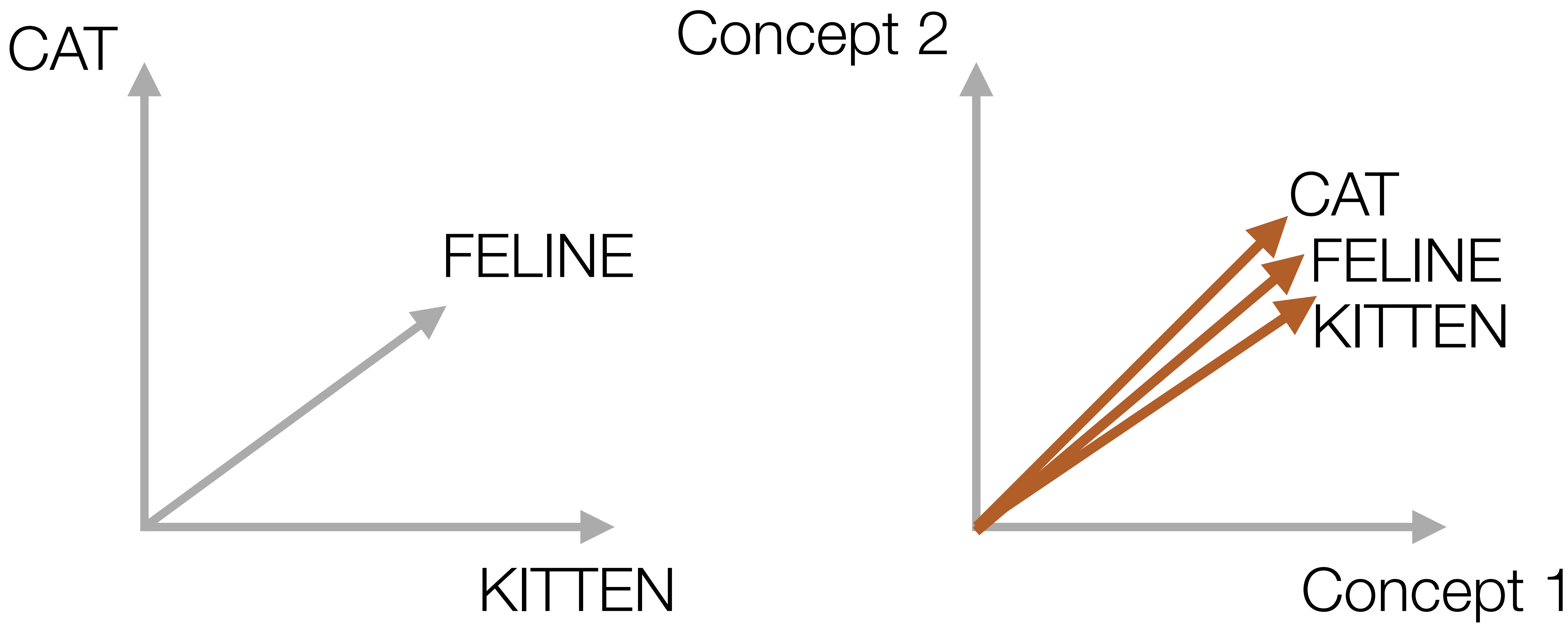
Dimensionality Reduction

- **Learned** dimensionality reduction can be easily achieved through a linear projection (potentially followed by a non-linearity)
    - e.g. a fully-connected layer

Learning Similarity: Distributional semantics

- **Distributional Hypothesis**:
  - **words that are close in meaning will occur in similar pieces of text**
- Exploit this to uncover *hidden meaning*
  - Latent Semantic Analysis
  - Word Embeddings

Concept Spaces/Semantic Spaces



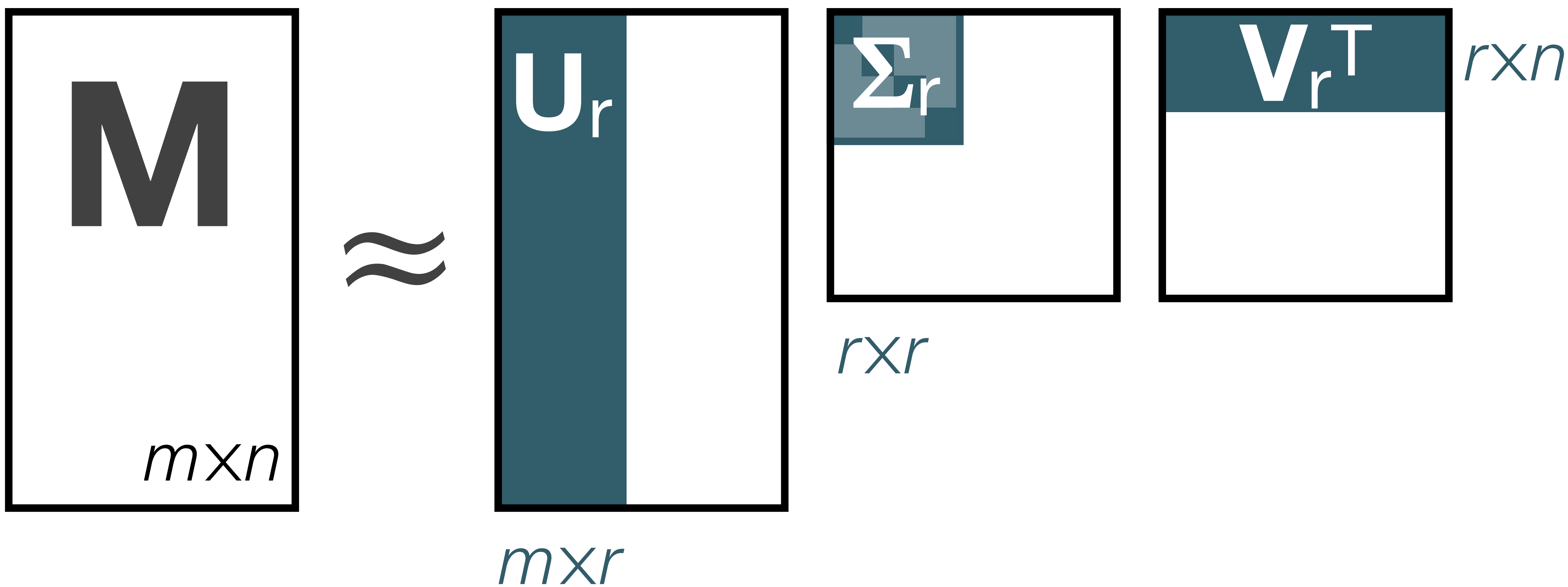
Latent Semantic Analysis

- Consider a **term-document matrix** which described occurrences of terms in documents
  - Clearly going to be sparse
  - Could be weighted (c.f. TF-IDF)

Latent Semantic Analysis

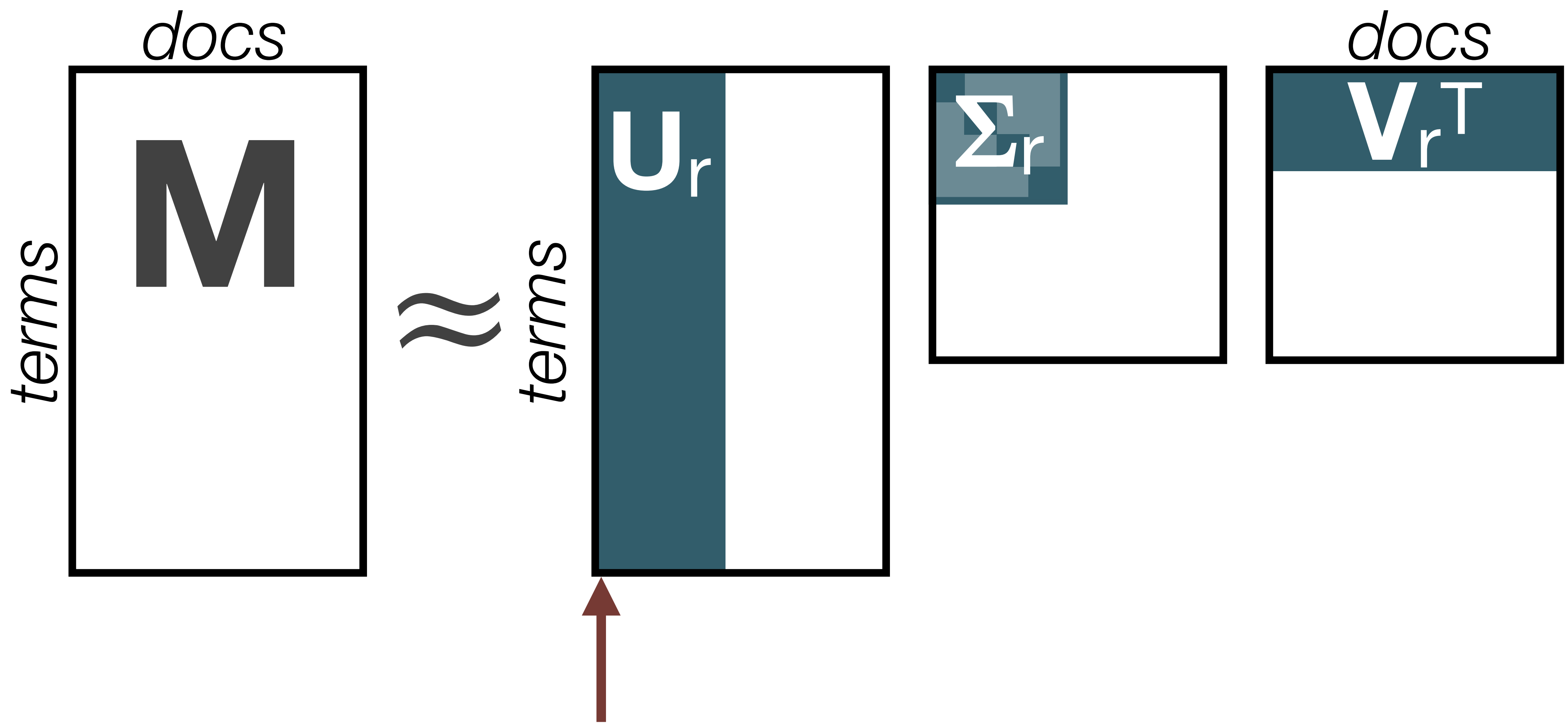
- LSA works by making a **low-rank approximation** under the following assumptions:
  - The original term-document matrix is **noisy**
    - anecdotal instances of terms are to be eliminated.
      - the approximated matrix is **de-noised**
  - The original term-document matrix is **overly sparse** relative to the "*true*" term-document matrix
    - We want to capture **synonymy**

Truncated Singular Value Decomposition



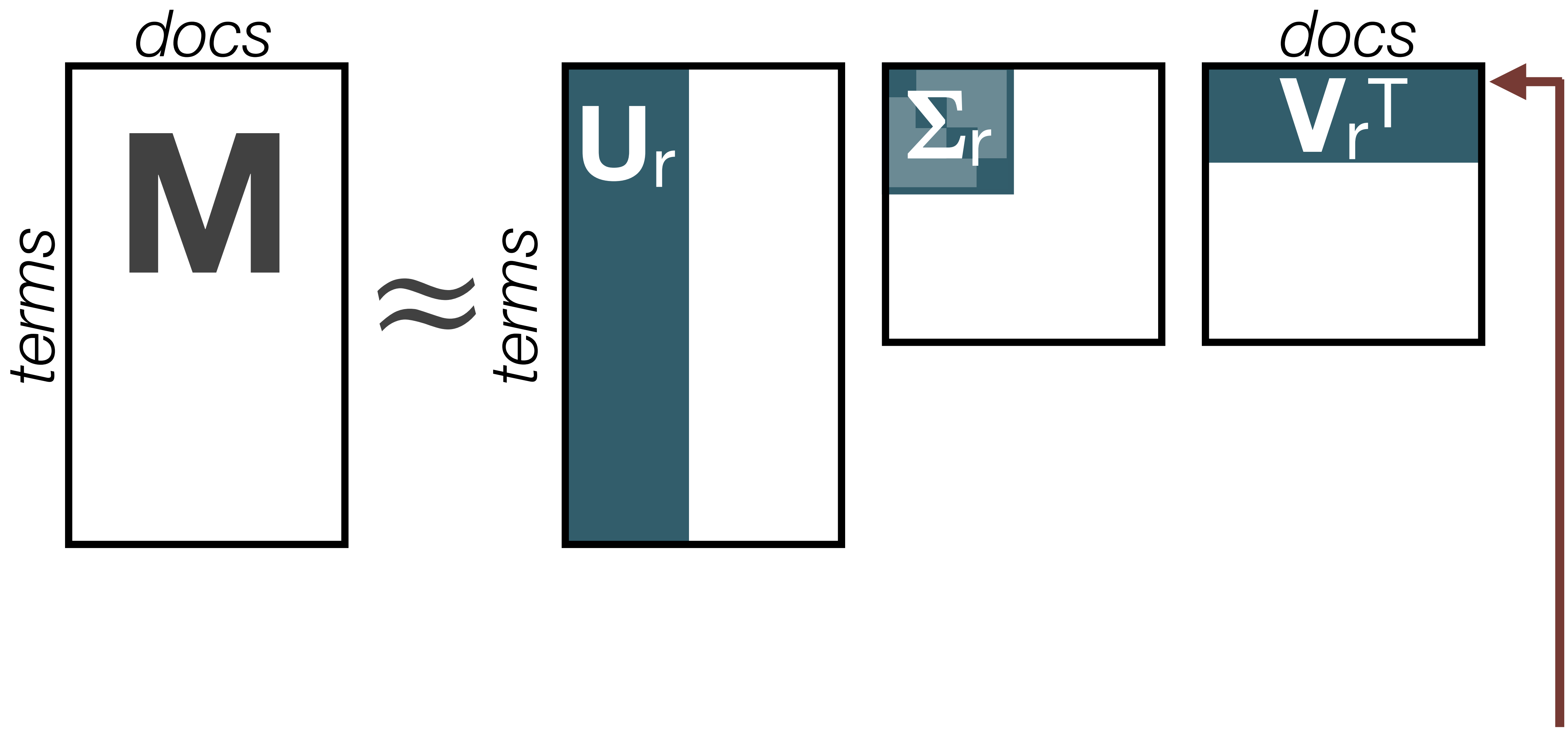
*Truncated SVD considers only the **largest** r singular values (and corresponding left & right vectors)*

Latent Semantic Analysis



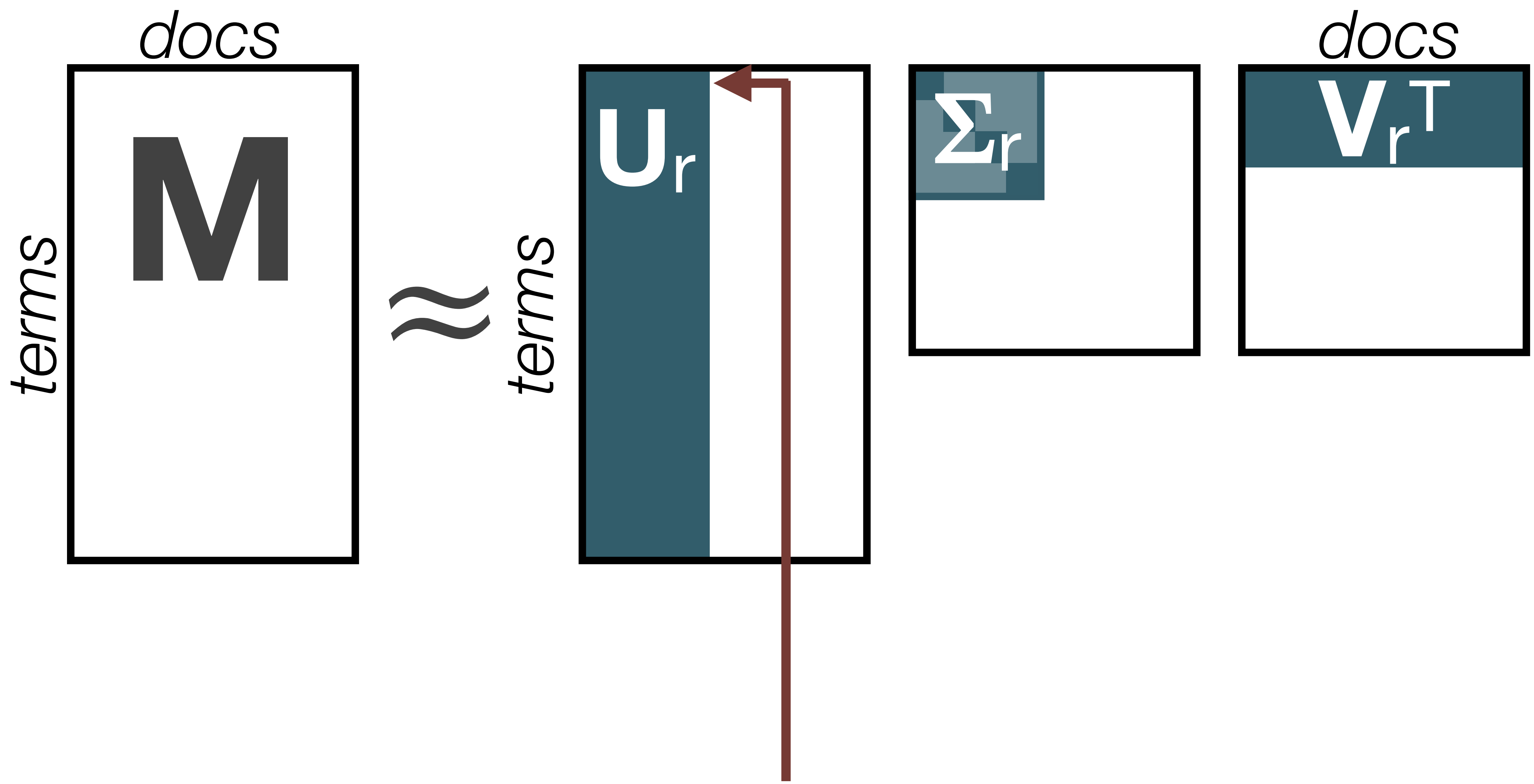
Each column corresponds to an eigenvector of $\mathbf{MM}^T$
(i.e. proportional to covariance or correlation of the terms)
*These are the "**concepts**"*

Latent Semantic Analysis



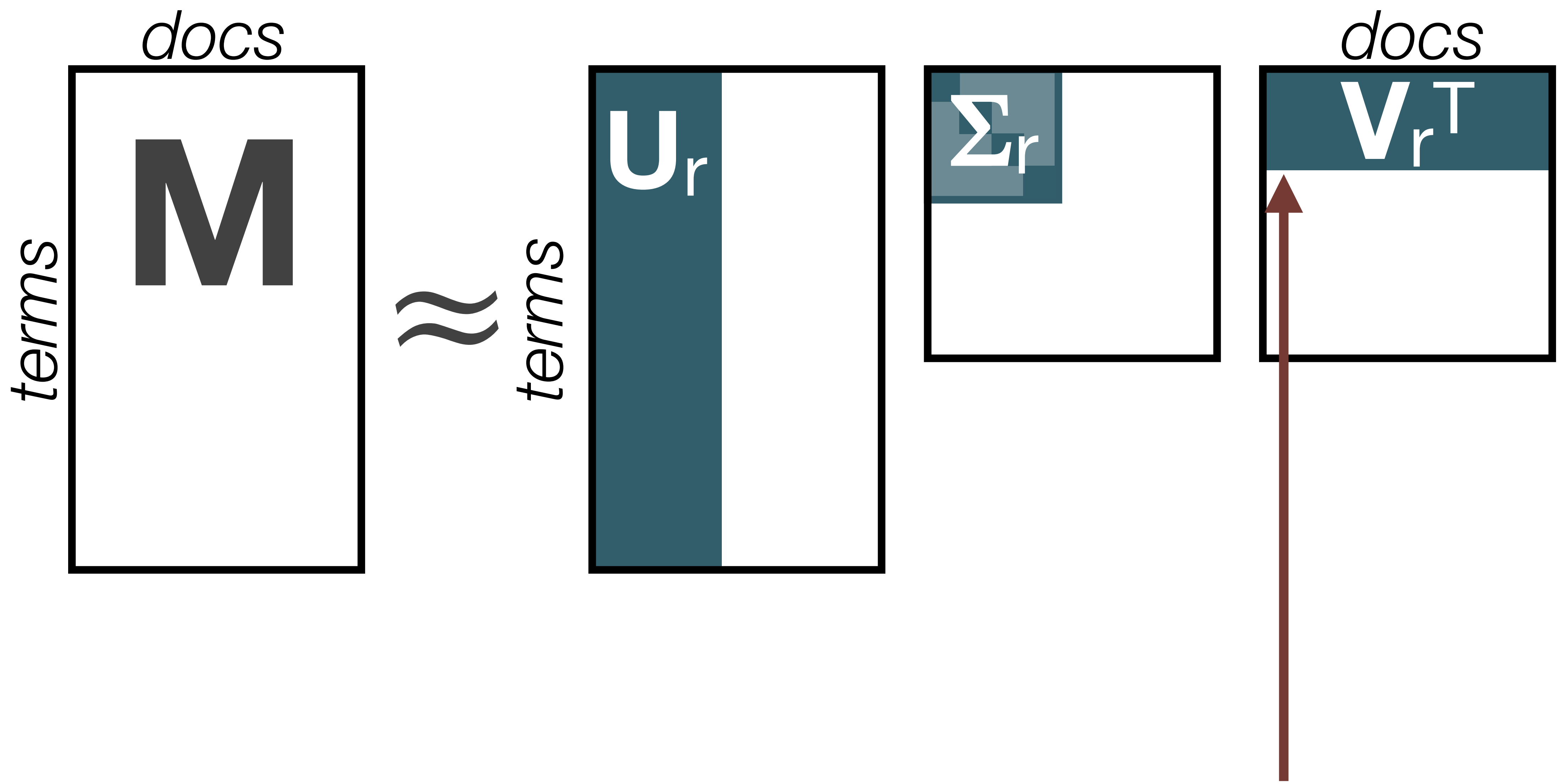
Each row corresponds to an eigenvector of **M^TM**
(i.e. proportional to covariance or correlation of the documents)
*These are the "**concepts**"*

Latent Semantic Analysis



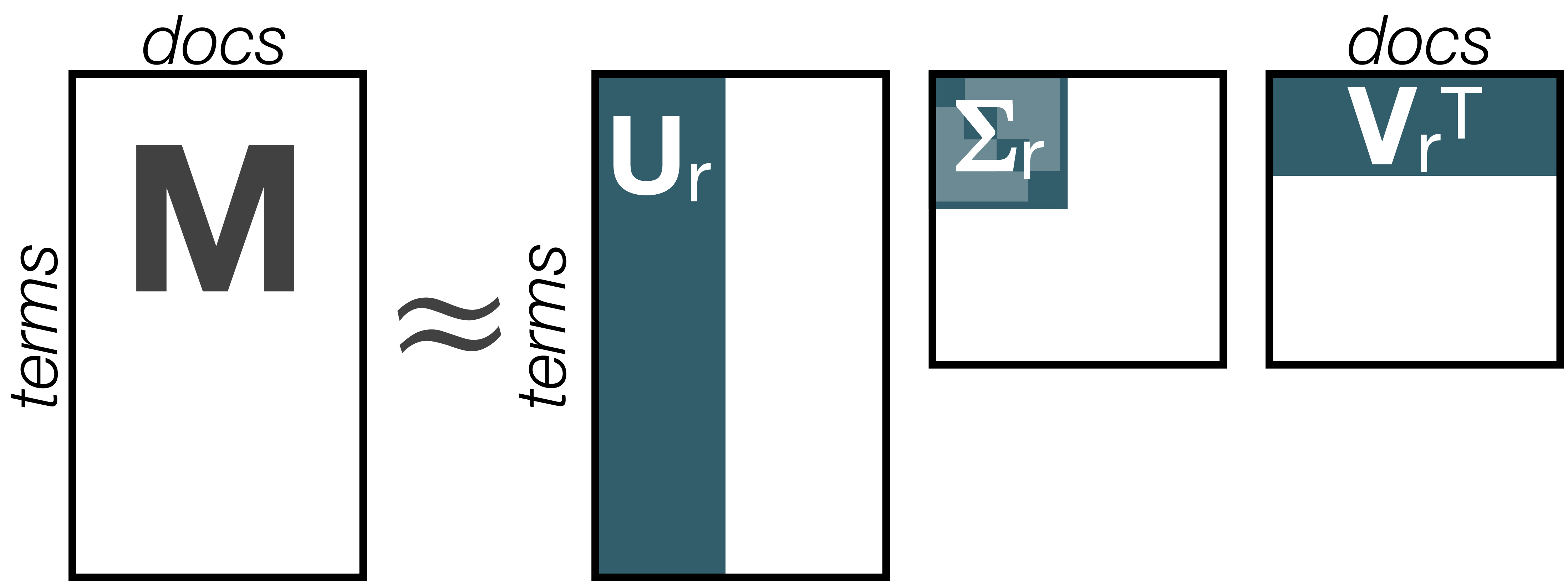
Each row corresponds to an r dimensional vector that describes a term as a vector of weights with respect to the r concepts

Latent Semantic Analysis



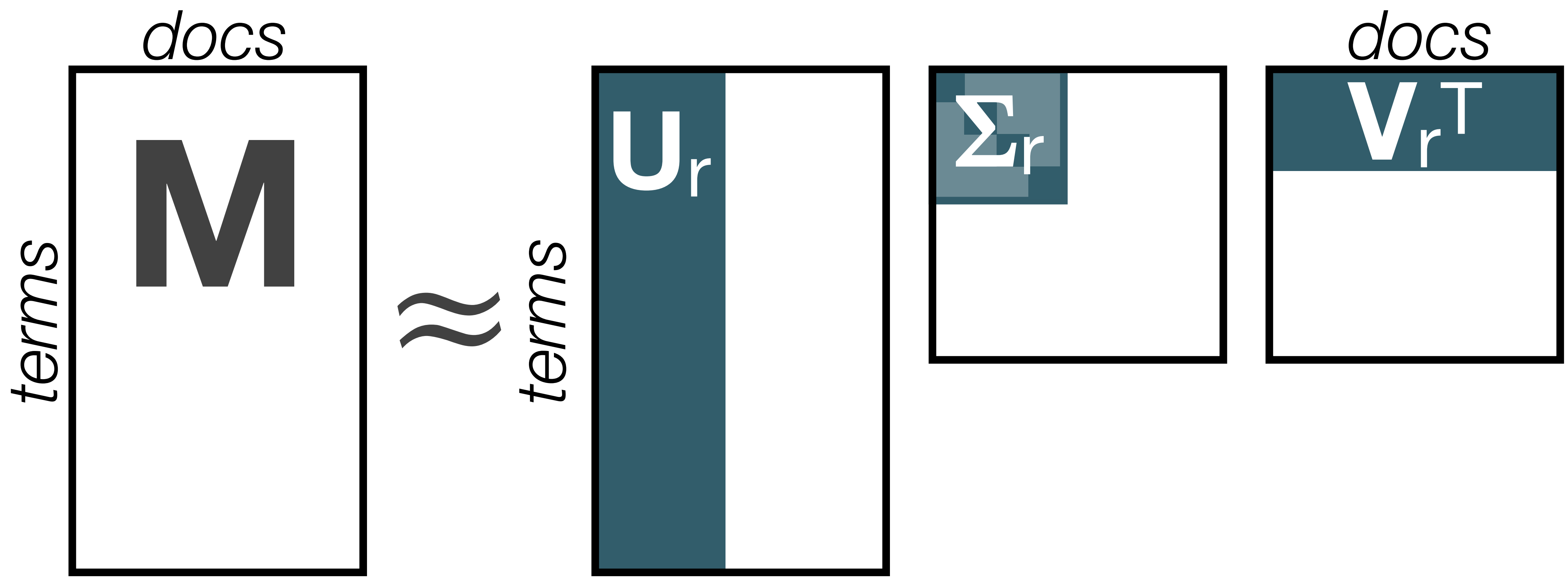
Each column corresponds to an r dimensional vector that describes a document as a vector of weights with respect to the r concepts

Important Note



The term-concepts and the document-concepts are not the same - they have the same dimensionality, but represent different spaces
They are intrinsically linked though, and it is possible to project one into the other

What exactly is a concept?



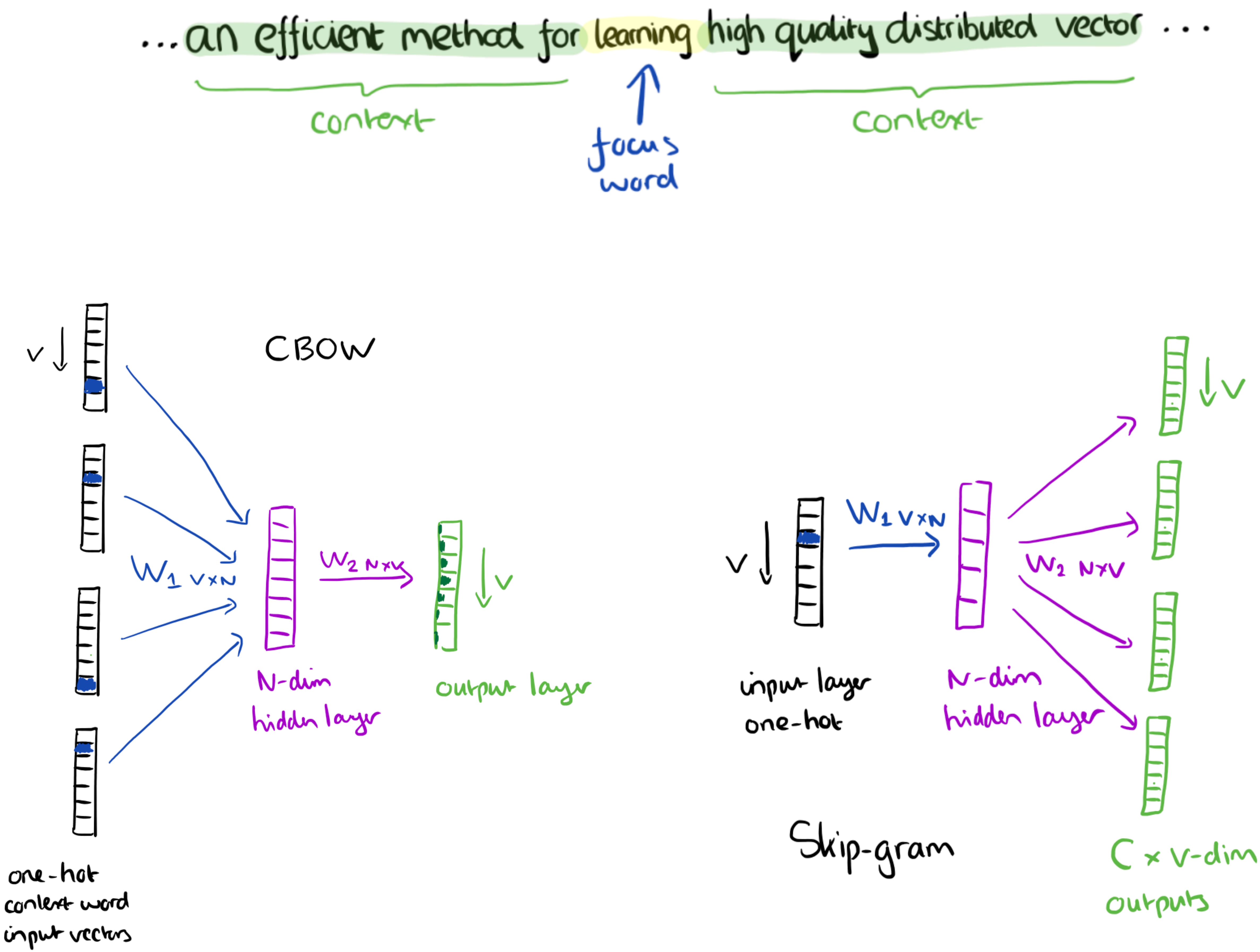
A linear combination of terms (or documents).
Not necessarily "comprehensible" -
*e.g. 1.3452 * **car** - 0.2828 * **bottle***

Word Embeddings

- Can we build a better vector representation of words?
  - Lower dimensionality (but dense)
  - Capturing synonymous words
  - What about capturing algebraic semantics?
    - word2vec(“Brother”) - word2vec(“Man”) + word2vec(“Woman”) = word2vec(“Sister”)

Word Embeddings…

- Many models of mapping words to vectors have been proposed.
    - A pair of commonly used models is known as “word2vec” and was introduced by Mikolov *et al.* at Google
        - They’re both shallow two-layer neural nets, but trained on *lots* of data
        - Ironically, although the paper introducing the models has over 27343 citations, it was never officially published after being rejected (and heavily slated by the reviewers) of ICLR 2013!
    - Another popular model is GloVe “Global Vectors for Word Representation” by Pennington *et al.*
    - All these models have all the features from the previous slides!
    - *Note that practically speaking, you don’t have to train the models - you can just download a pretrained variant*



Images from https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

word2vec limitations

- word2vec works well, but doesn’t deal with out of vocabulary (OOV) words
    - A newer model called FastText attempts to solve this problem by building the embeddings from character n-grams
        - The idea is that words with similar meaning often have similar sub-strings (e.g. locat[e/ing/ion])

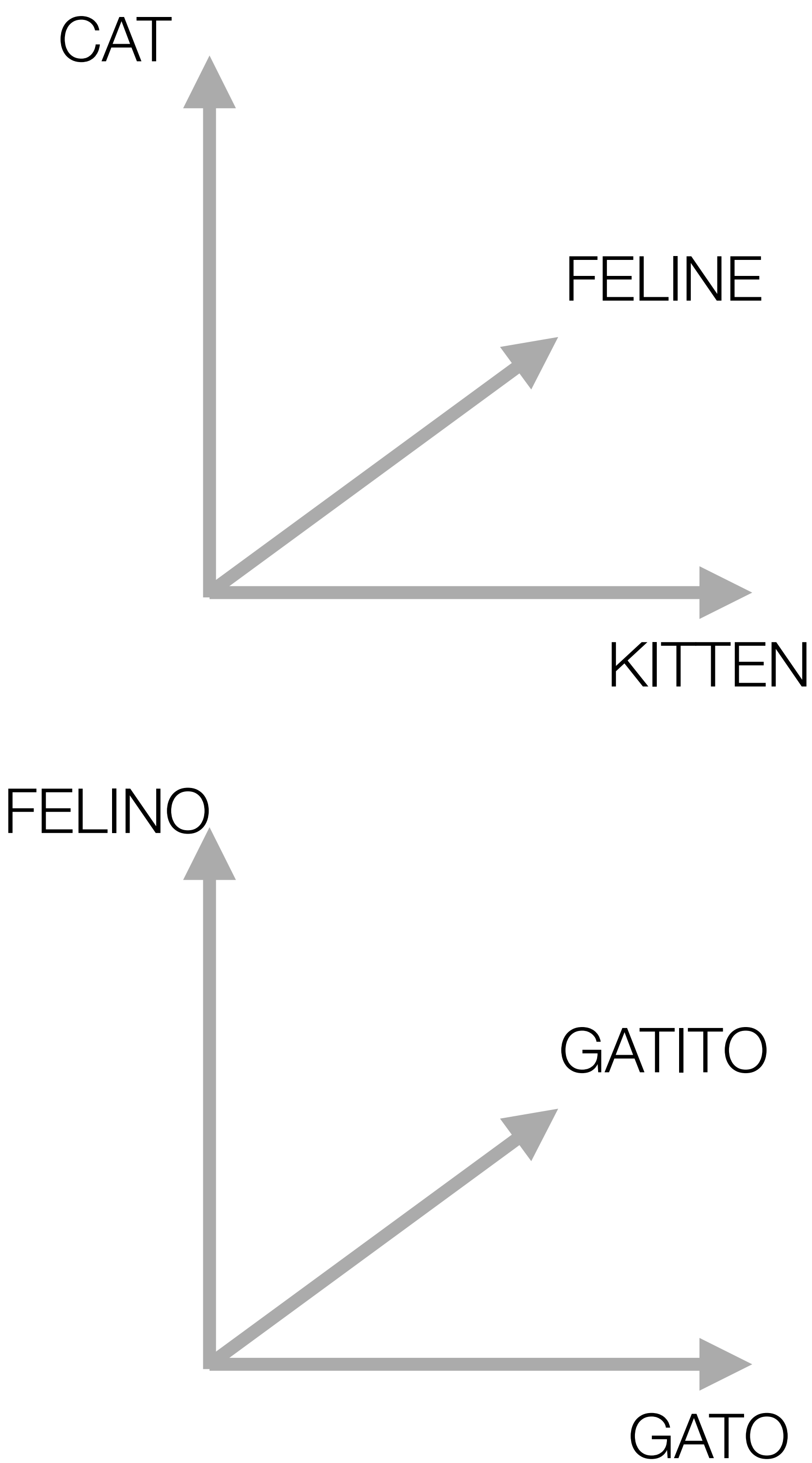
Implementation Note

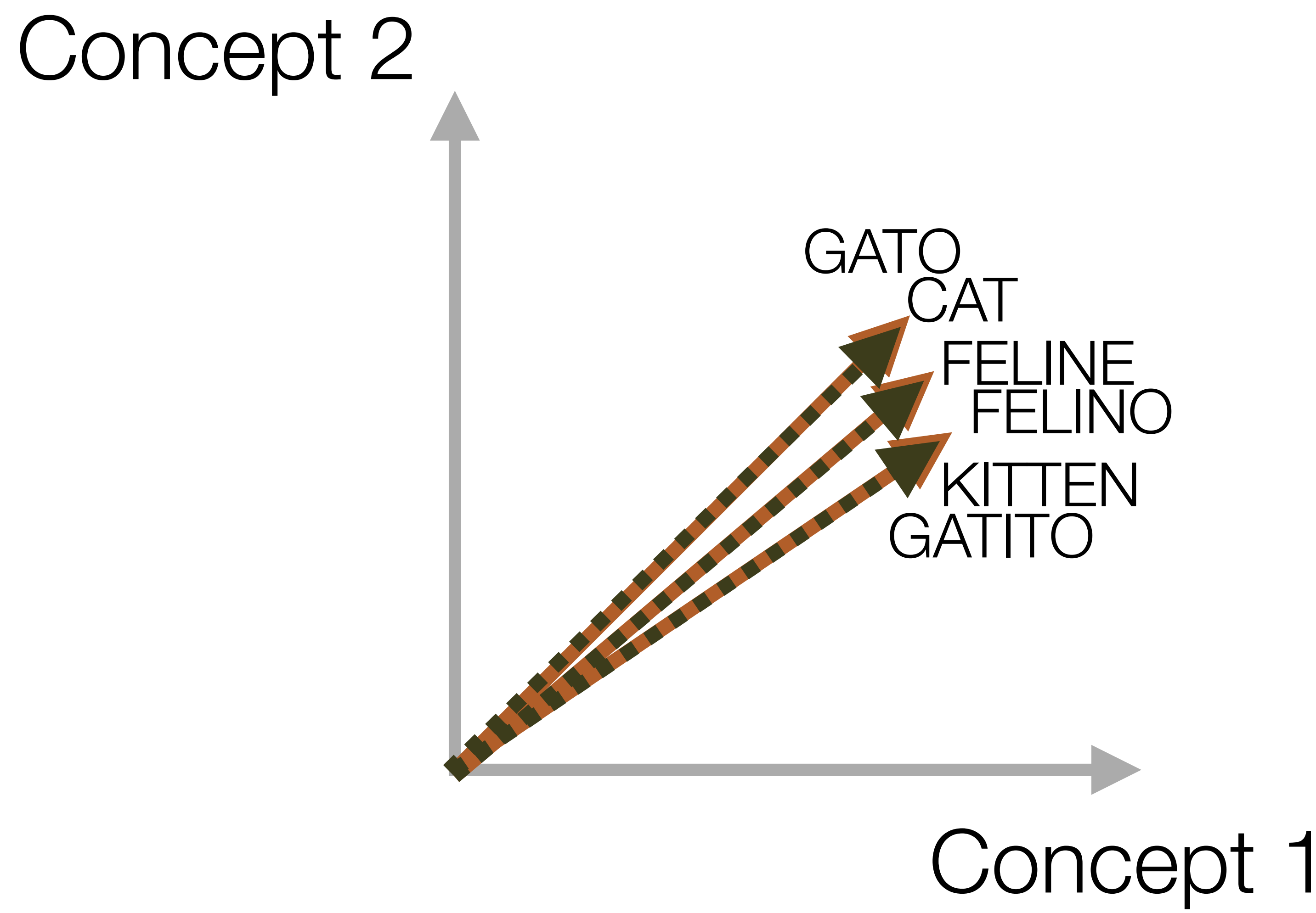
- In PyTorch, we don’t ever represent a word in one-hot form
  - Too expensive & unnecessary
  - Rather, the **Embedding Layer**, is implemented as a lookup-table between the input word index and the corresponding output vector
    - Can still be differentiated though of course as it’s functionally equivalent to multiplication of the layer weights by an OHE vector

Embedding Layer

Mining semantic correspondences across feature domains

Embedding across languages





Cross-Language LSI

- Use a bilingual (or multilingual) **training** corpus to build a single term-document matrix
  - each document vector contains terms from the original language and its translation(s)

	CAT	KITTEN	FELINE	FELINO	GATO	GATITO	…
doc1	1	0	0	0	1	0	…
doc2	1	1	1	1	1	1	…
…							

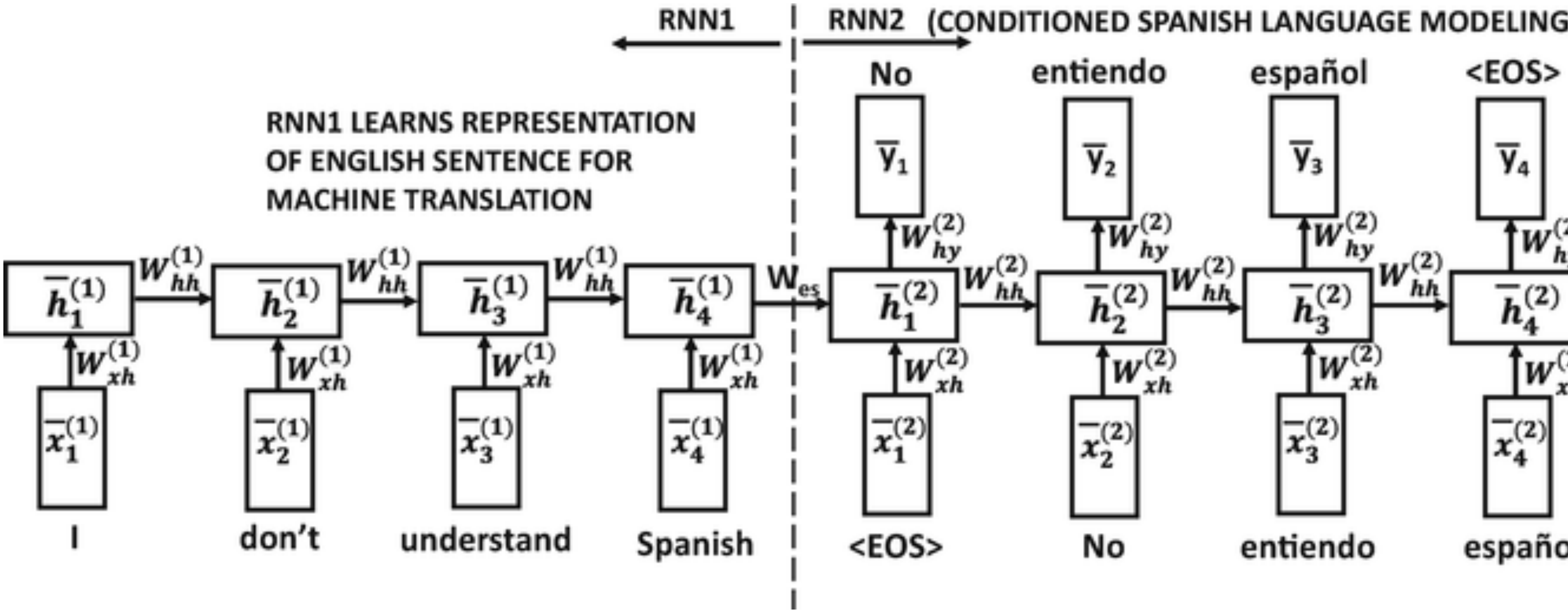
Cross-Language LSI

- Decompose with SVD as per standard LSI
- Perform queries by projecting into the lower dimensional space as before
  - but just use one language and set the rest to 0

	CAT	KITTEN	FELINE	FELINO	GATO	GATITO	…
query	1	0	0	0	0	0	…

  - Obviously this still has a problem in the sense that all the indexed documents needed translation…

Sequence-Sequence Translation



https://link.springer.com/chapter/10.1007/978-3-319-73531-3_10

Image-Concept Embedding

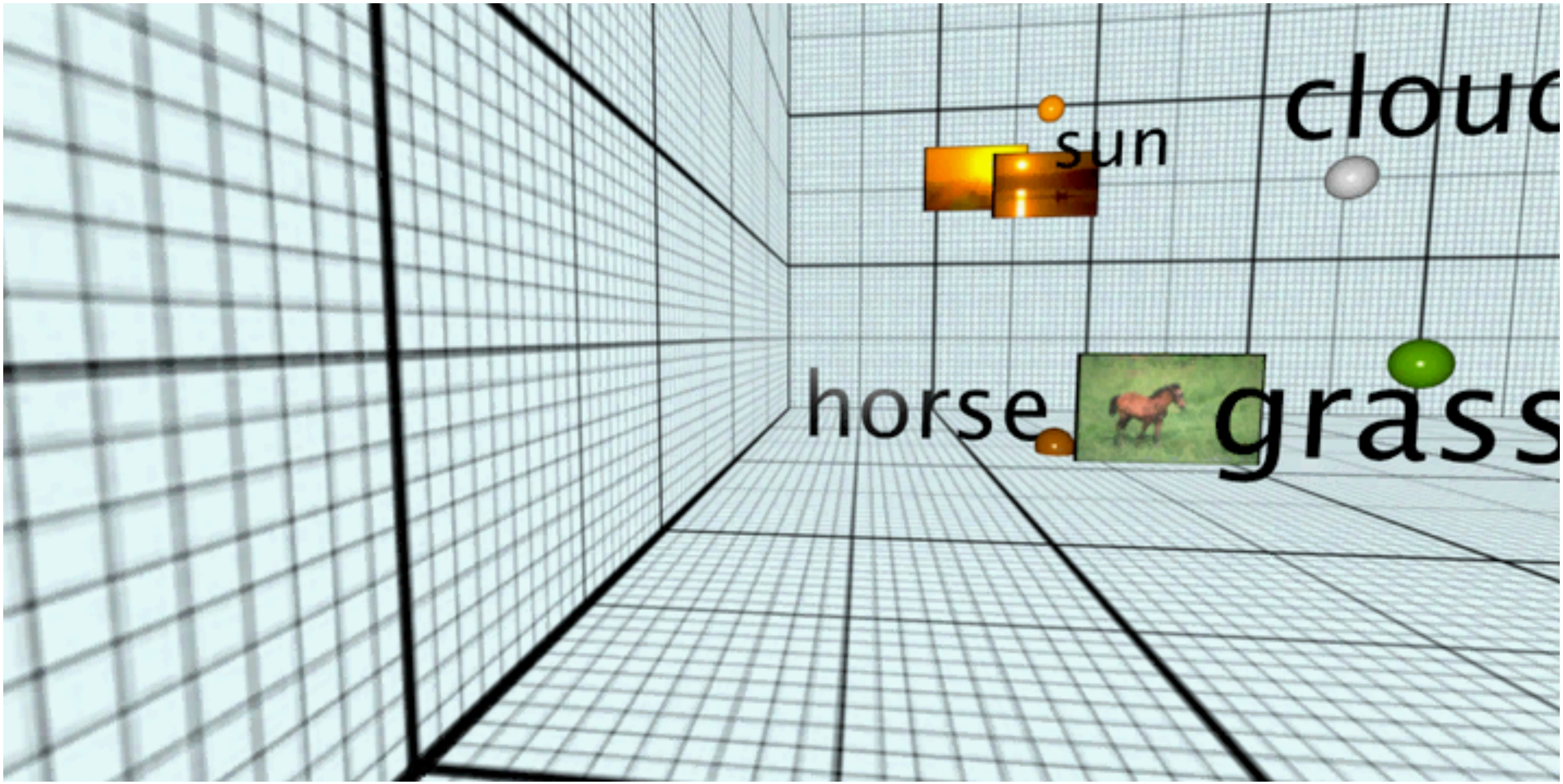
- Basic idea: Create a large multidimensional space in which images, keywords (or other metadata) and visual information can be placed.

- In the training stage learn how keywords are related to visual terms and images.

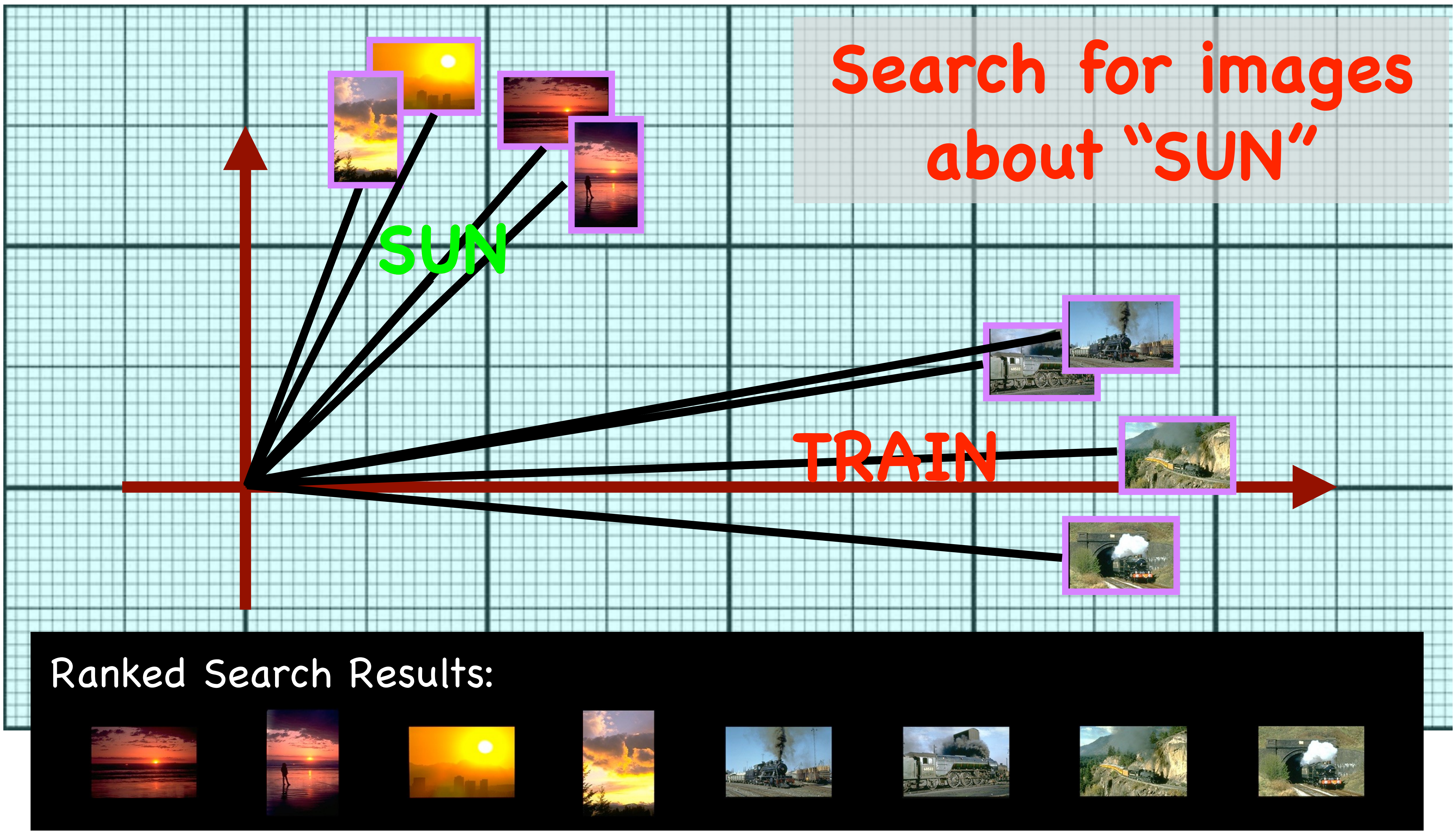
  - Place related visual terms, images and keywords close-together within the space.

- In the projection stage unannotated images can be placed in the space based upon the visual terms they contain.

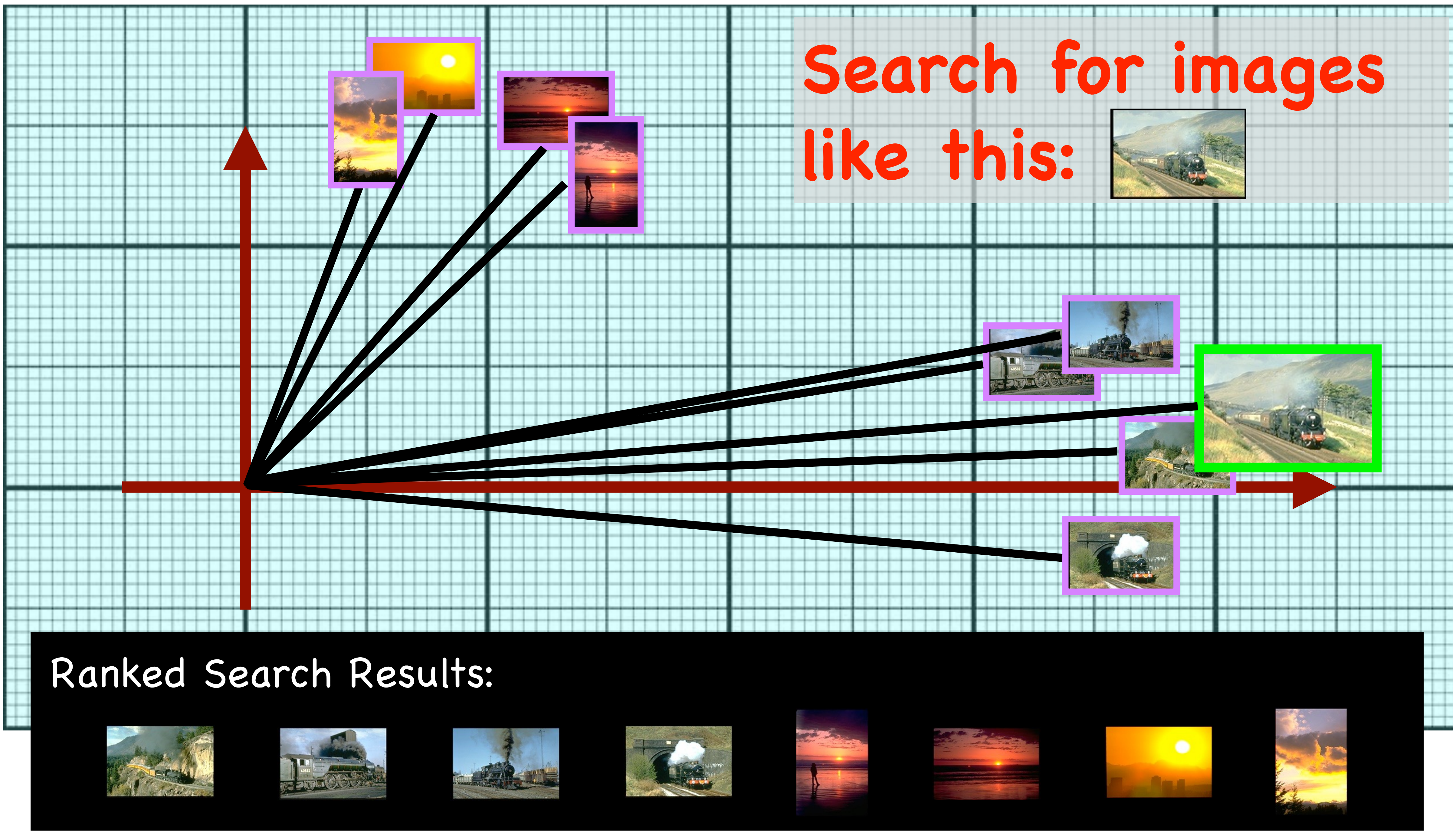
  - The placement should be such that they lie near keywords that describe them.


sun
clouc
horse
grass

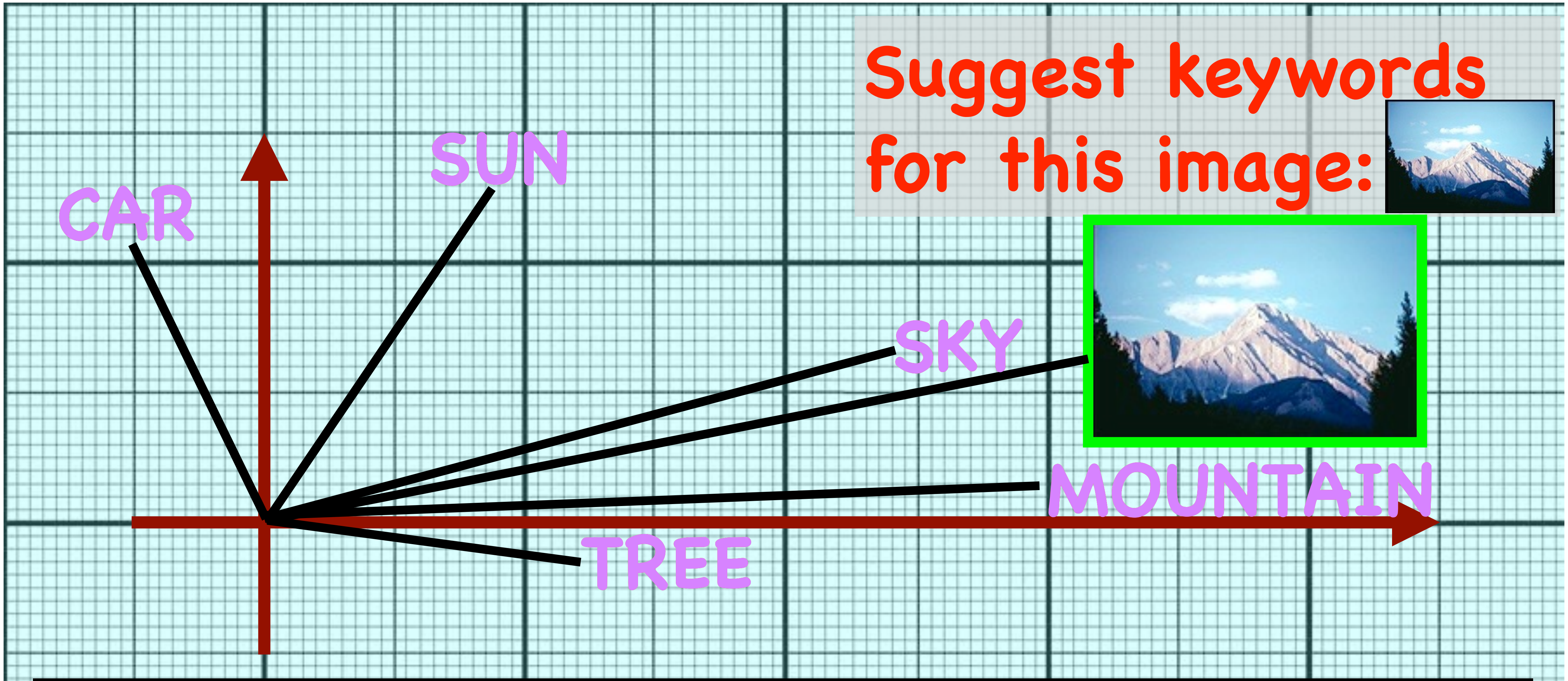
Searching by Keyword



Searching by Image



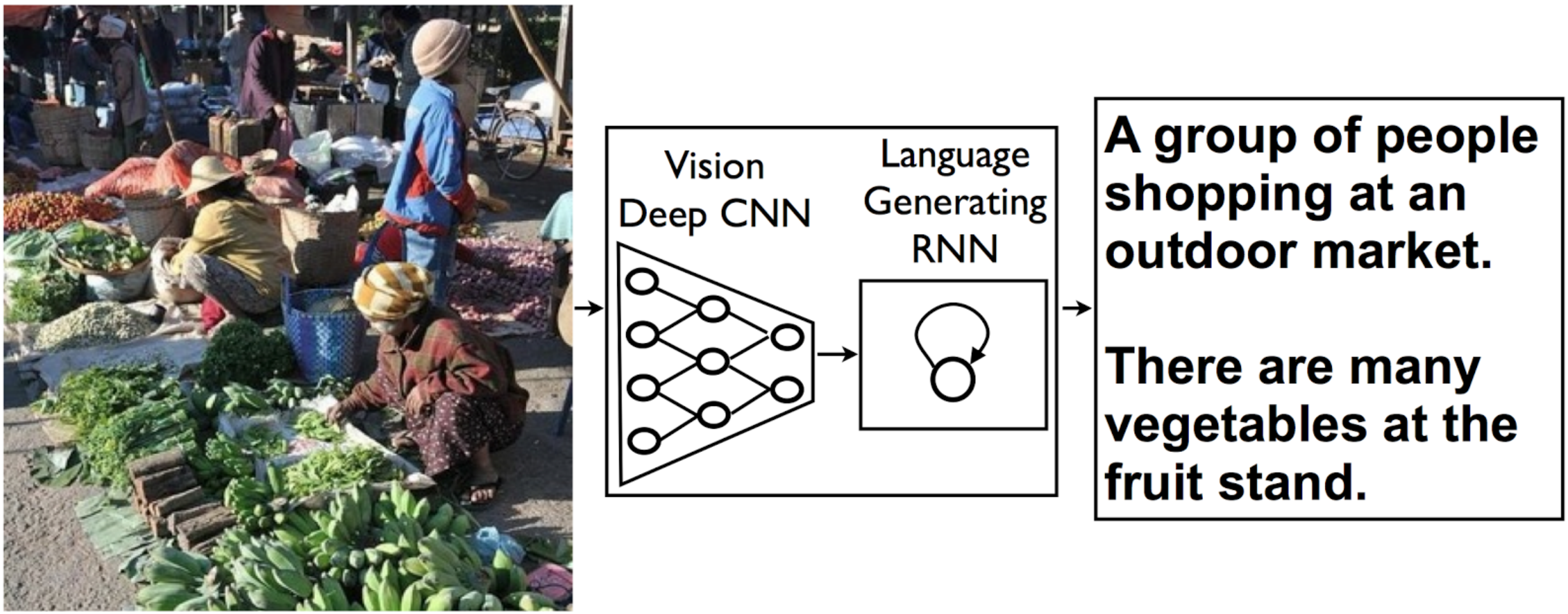
Suggesting Keywords



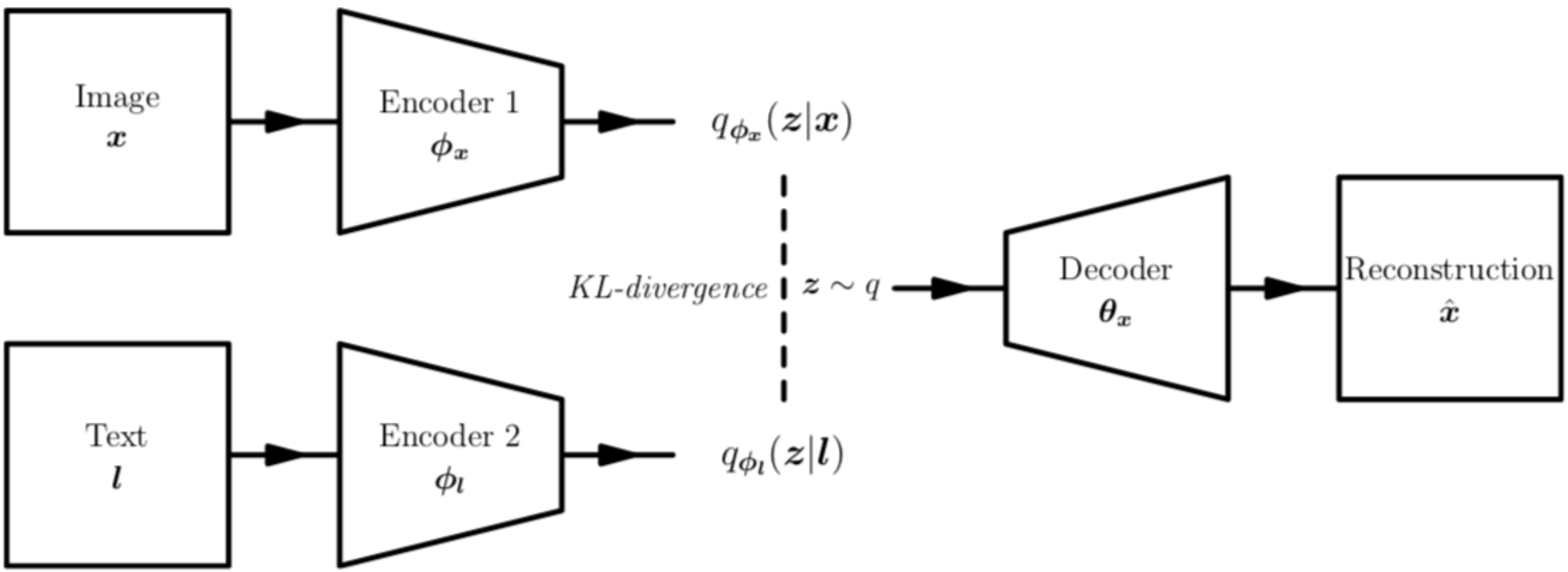
Suggested keywords:

SKY MOUNTAIN TREE SUN CAR

Image captioning



Probabilistic Semantic Embedding



https://openreview.net/pdf?id=r1xwqjRcY7