Embeddings

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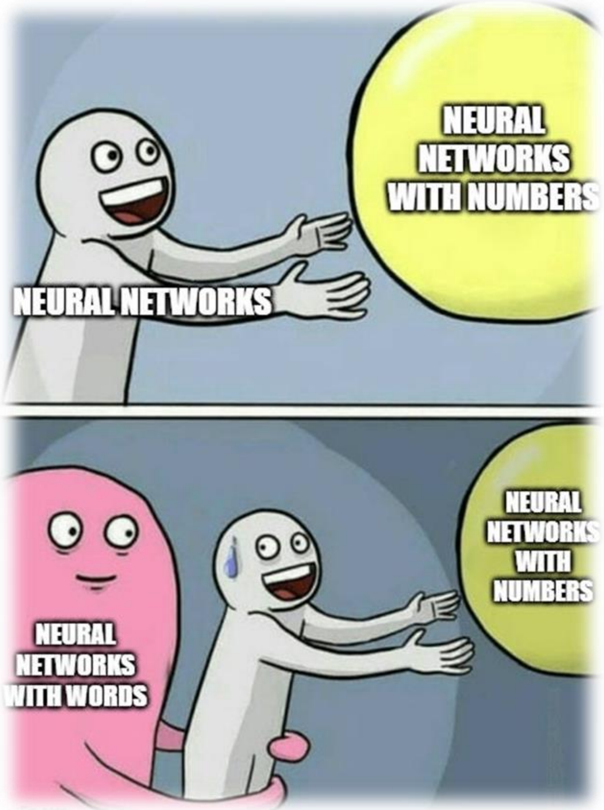
Outline

- Embeddings
- Building embeddings
- Embeddings from trained deep networks
- Embeddings with Autoencoders
- Embeddings of Vocabularies

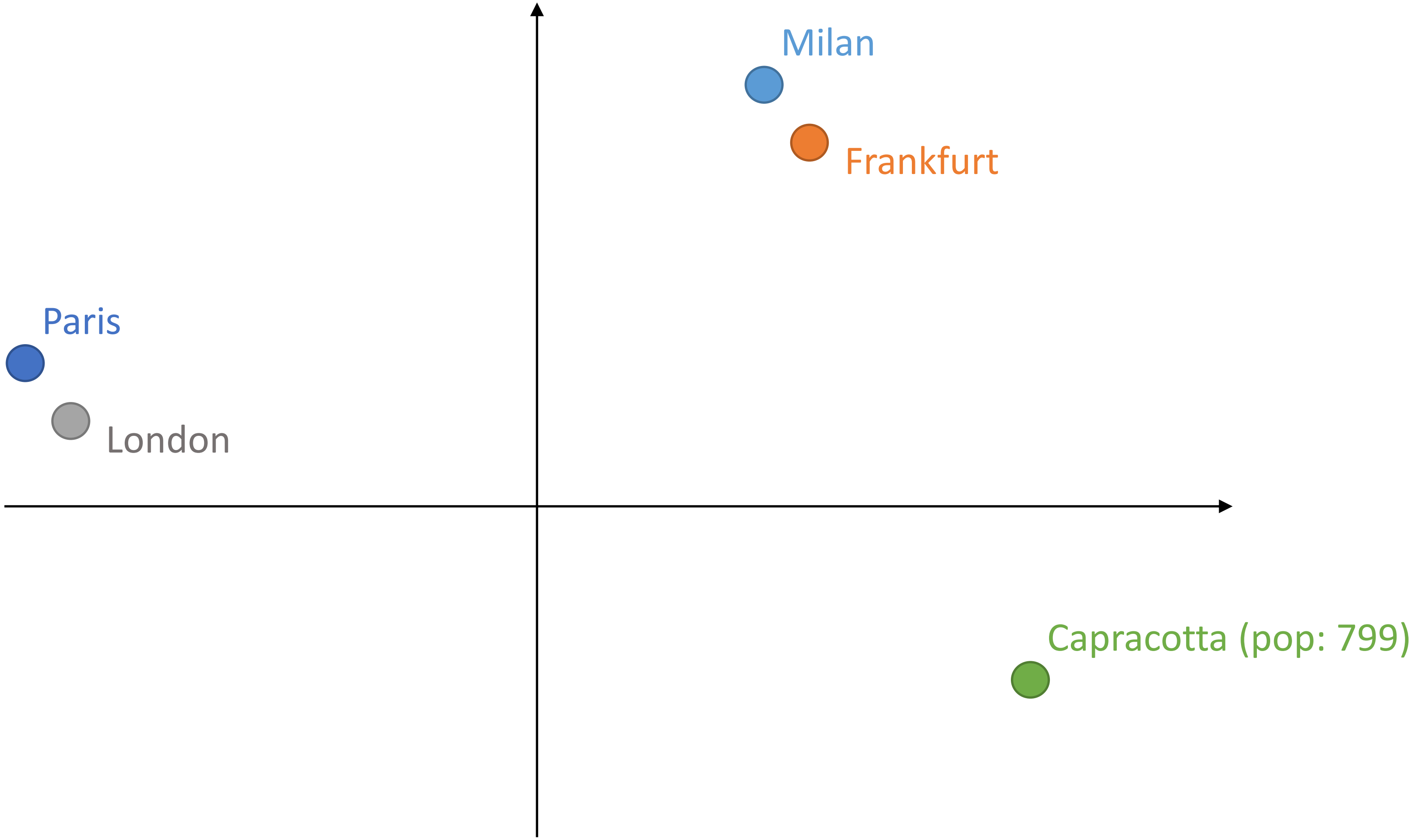


Embeddings

- Curiously, an embedding is not necessarily related to DL
- An embedding is a **vectorial space**, $\boldsymbol{x} \in \mathbb{R}^d$ with semantics
  - Distances and relative positions between points have a *meaning*
  - And displacements/transformations might also have meaning
  - Vocabulary clash, “vector”/“point”

- Let’s build an embedding! Meaningful dimensions for **cities**?

Embedding for cities

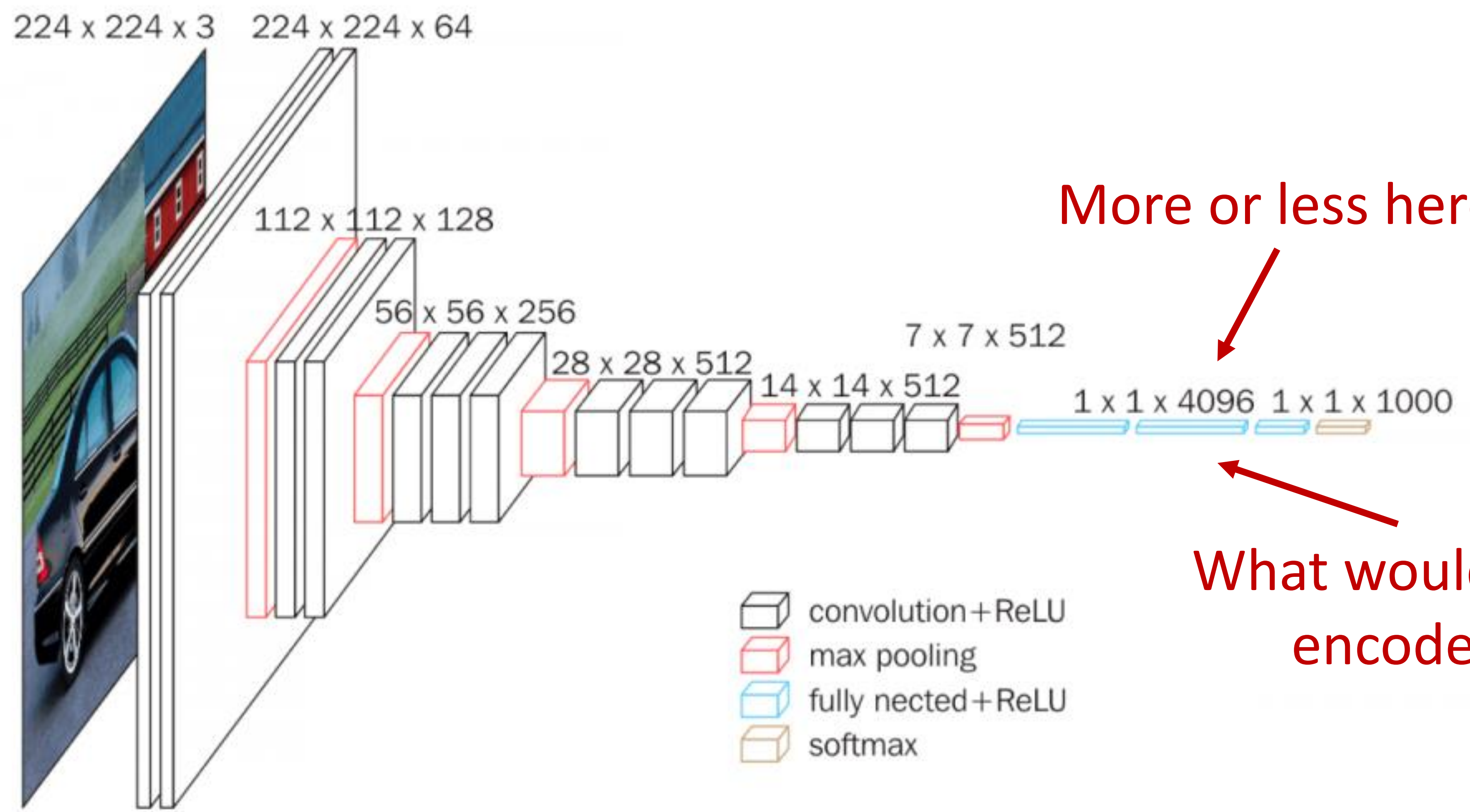


Building embeddings

- Building embeddings is pretty *hard*
  - Already when we have meaningful features
  - But for **relational data**? Pixels, words, videos, sound, …?

- Supervised task in DL architecture *might* create embedding
  - Output of a (deep) module can be interpreted as vectorial space
  - Encoding **meaning related to supervised task**

Embeddings from trained deep networks



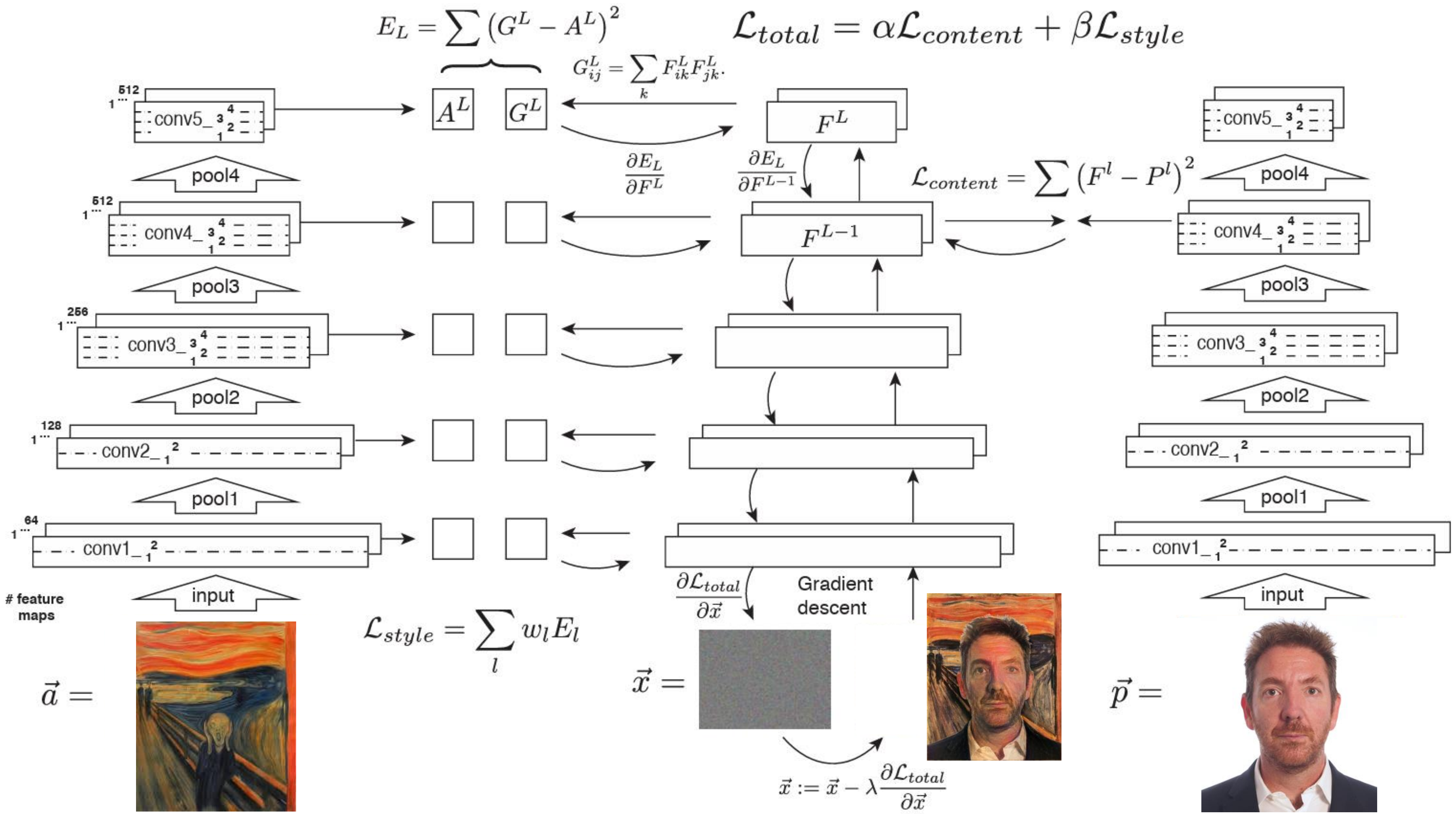
More or less here

What would this encode?

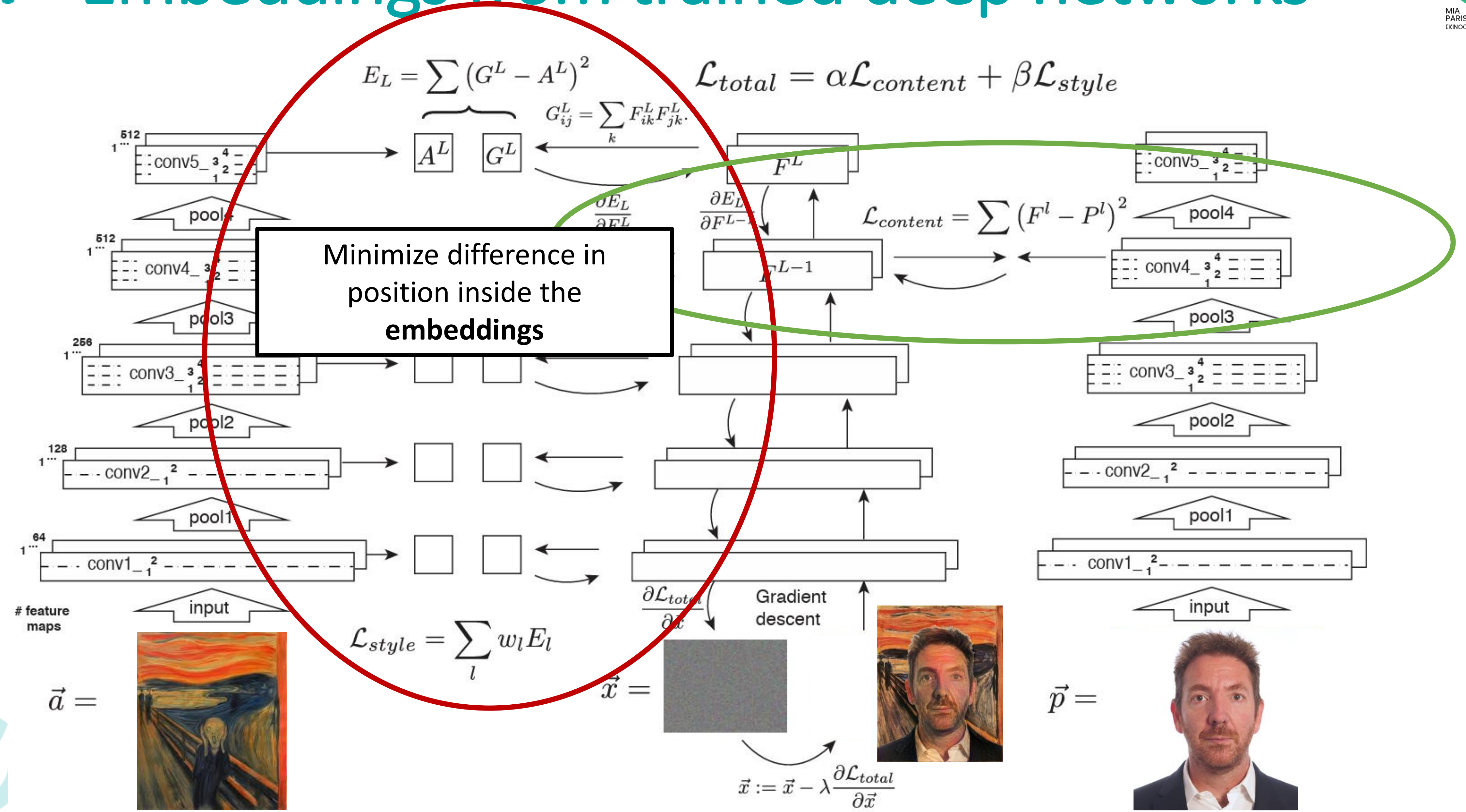
Embeddings from trained deep networks

- Taking VGG-16, output of deep modules
  - Might encode samples of same class close together
  - If we are lucky, samples of *visually similar classes* close together
  - However, encoded meaning related to **visual aspects**, only
  - Photo of bear and tiger very different, both ferocious predators

Embeddings from trained deep networks



Embeddings from trained deep networks



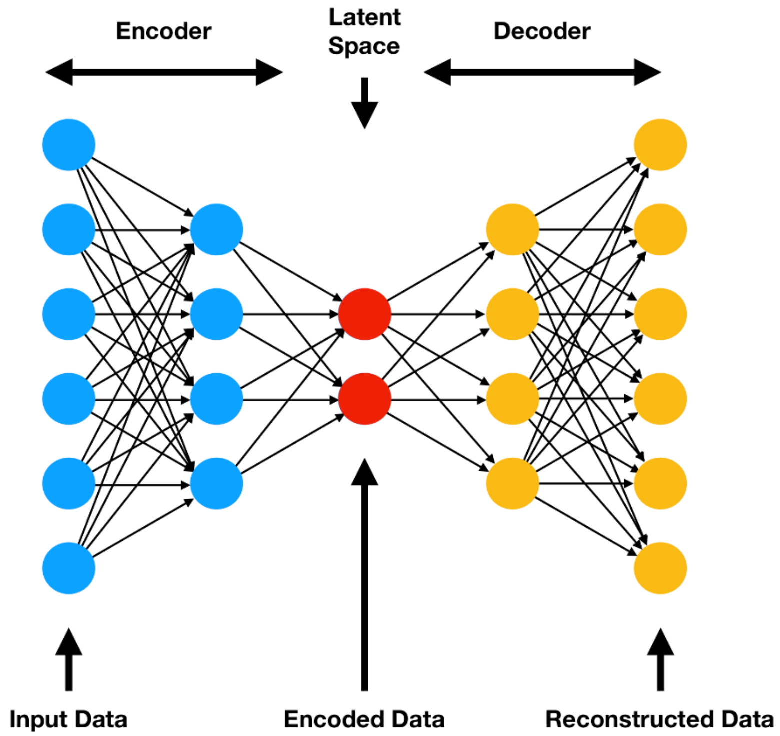
Minimize difference in position inside the **embeddings**

Embeddings, no tasks?

- What if do not have a task, or a ground truth?

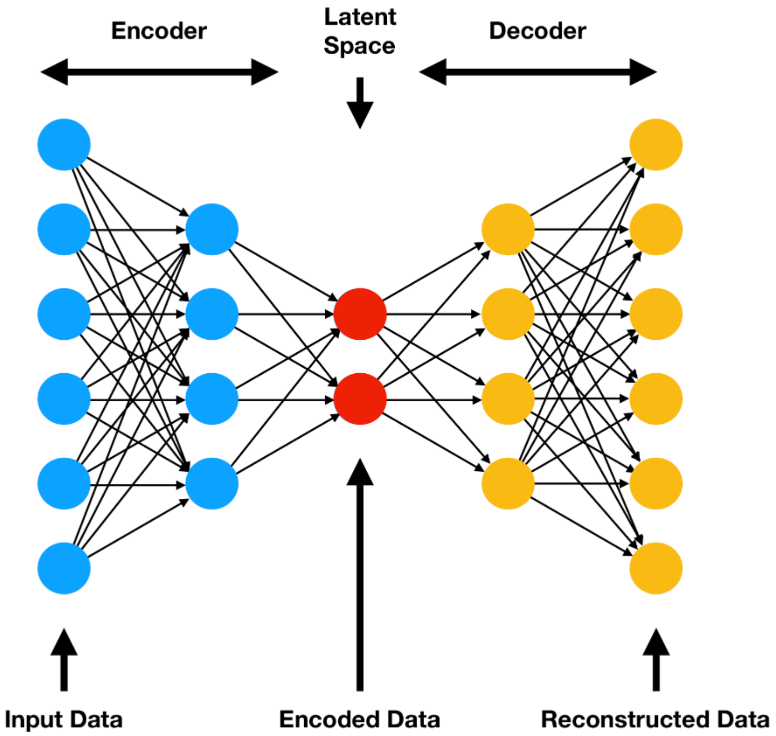
Embeddings with Autoencoders

- Deep learning architecture
  - Series of modules with less and less output dimensions
  - A bit like the "funnel" in CNNs
  - Module in the middle, lowest dimension
  - Second part, "funnel out"
  - Back to the original dimension of input
- Loss function: difference input-output
  - What does it mean?

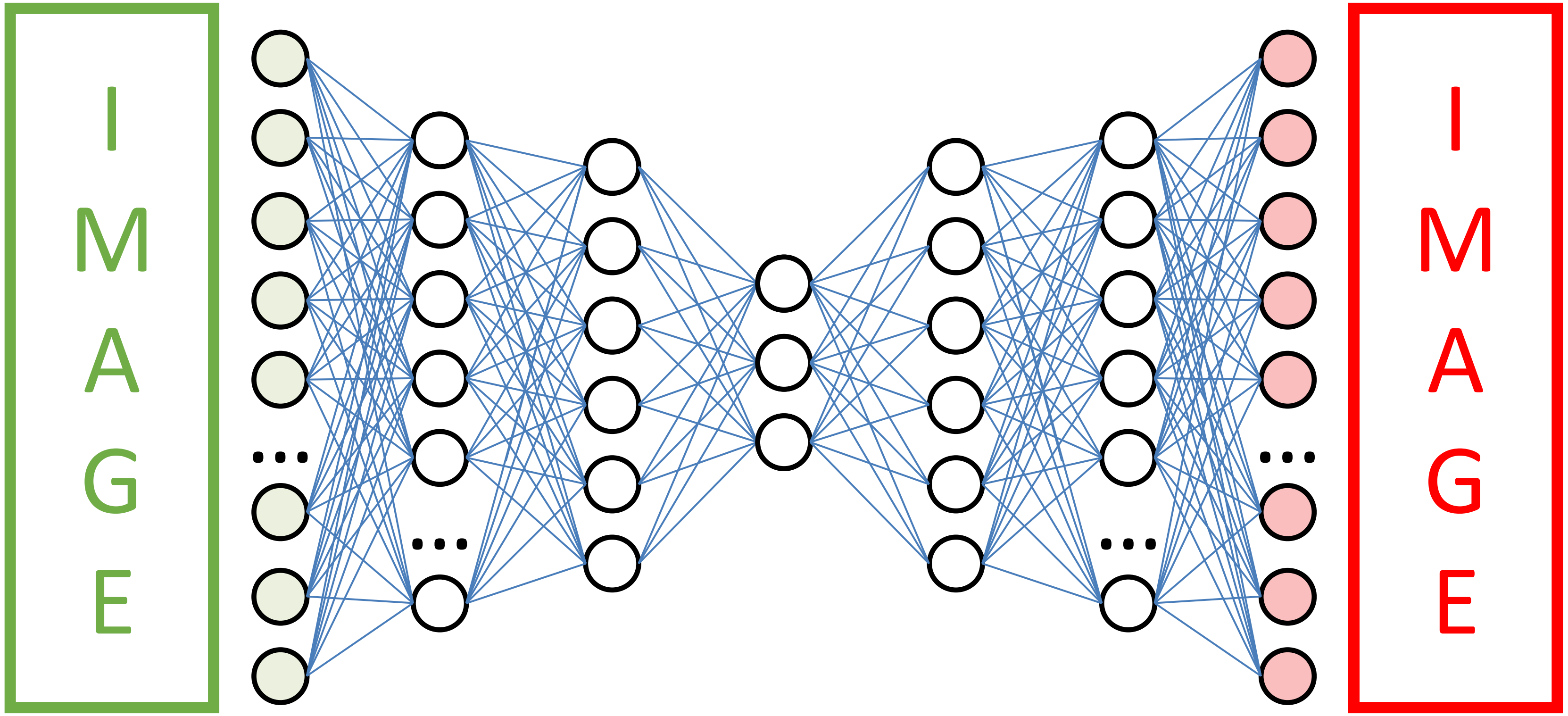


Embeddings with Autoencoders

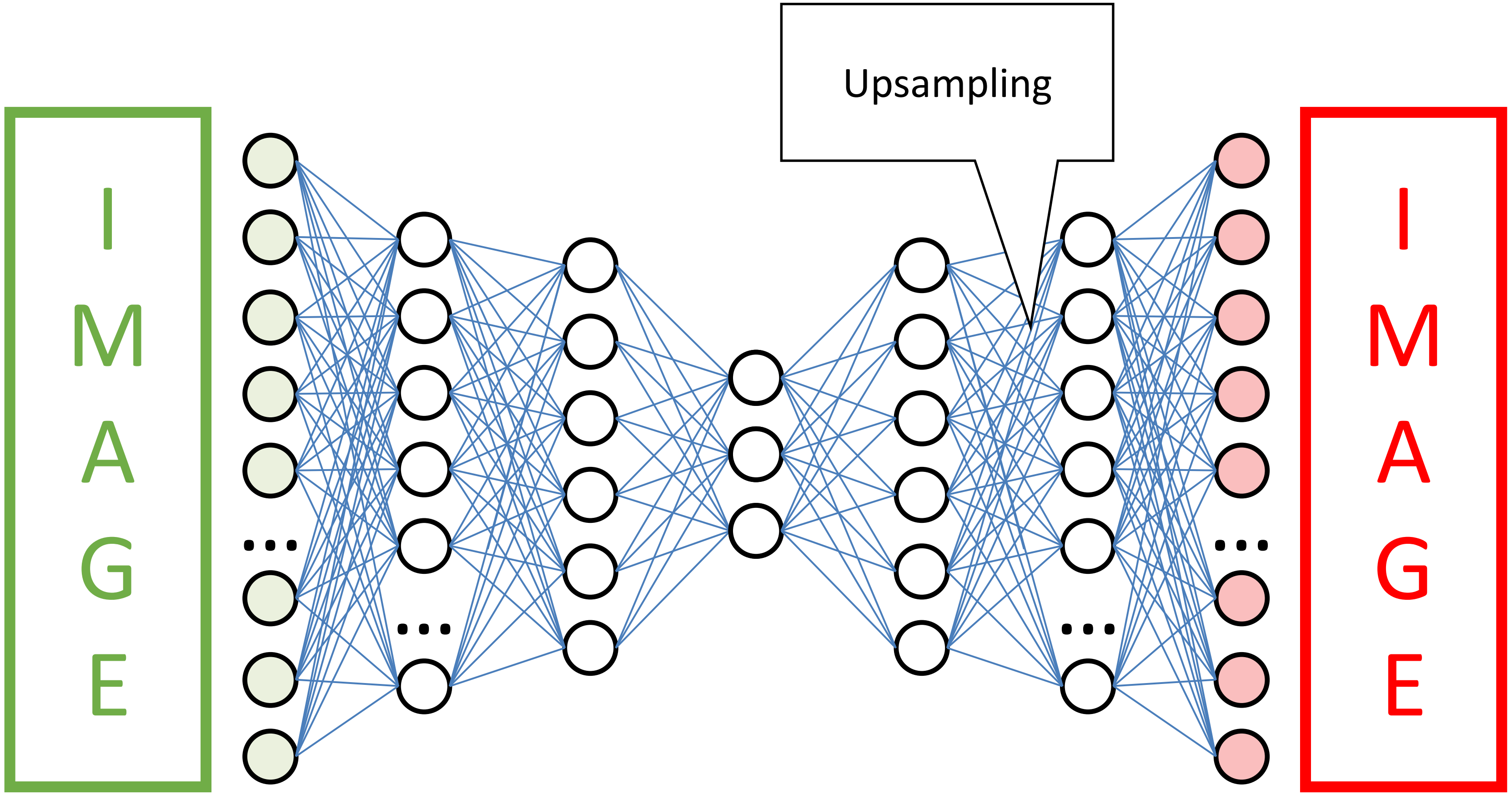
- Deep learning architecture
  - Series of modules with less and less output dimensions
  - A bit like the “funnel” in CNNs
  - Module in the middle, lowest dimension
  - Second part, “funnel out”
  - Back to the original dimension of input
- Loss function: difference input-output
  - Dimensionality reduction
  - **Meaningful**, to be able to reconstruct



Embeddings with Autoencoders

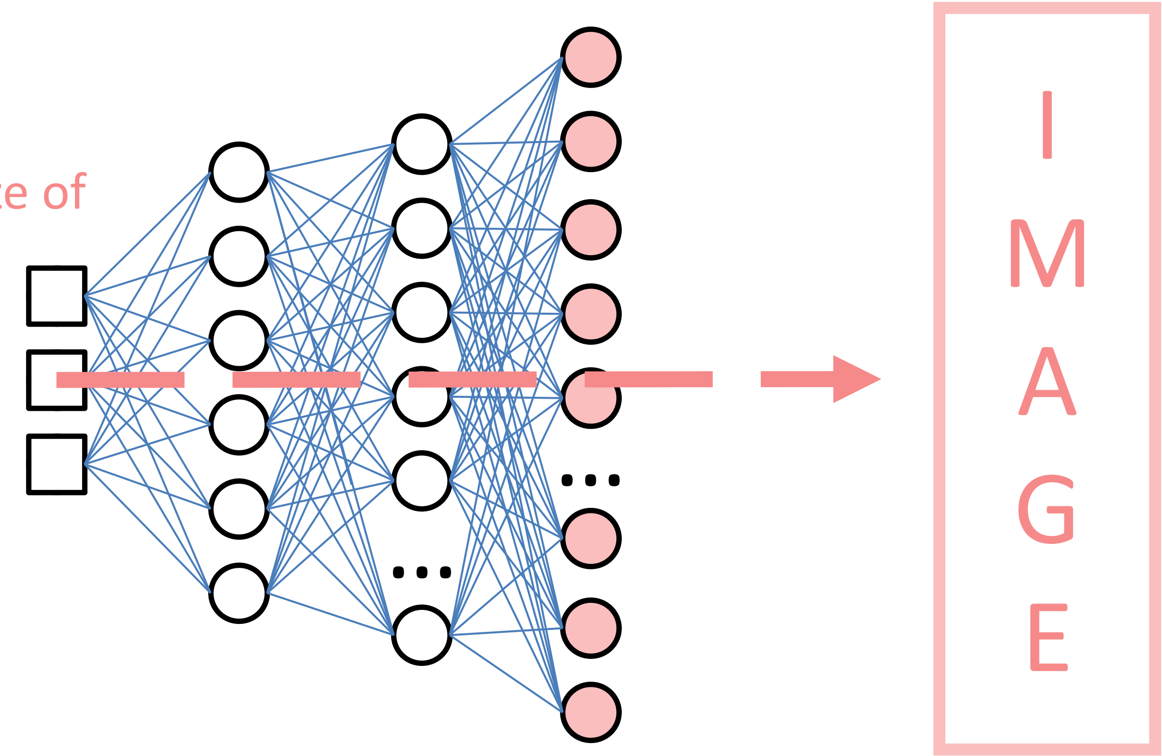


Embeddings with Autoencoders



Embeddings with Autoencoders

Random tensor of same size of the module output



Embeddings with Autoencoders

Embeddings with Autoencoders

- Two different points (vectors) in the same embedding…

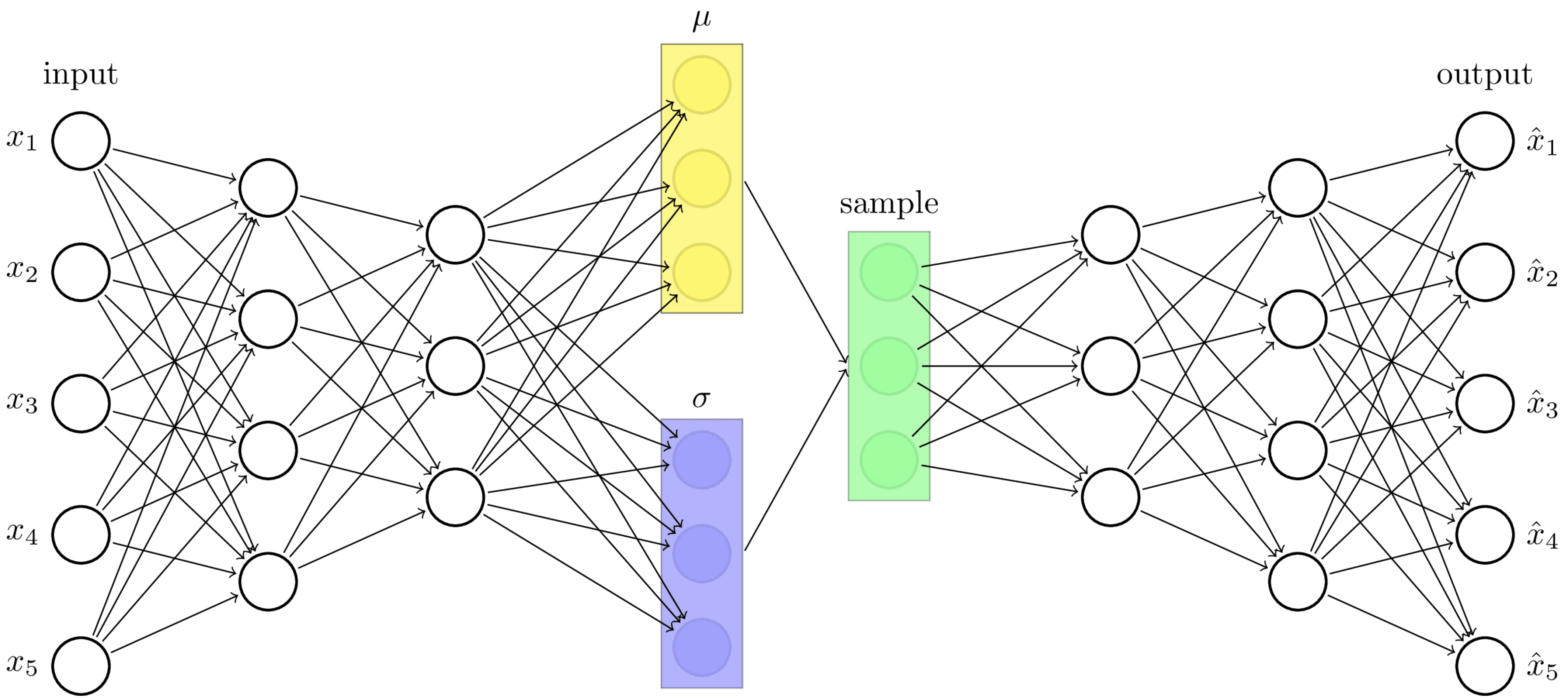
Embeddings with Autoencoders

- The latent space is brittle, full of “holes”
- Can we force this latent space to behave better?
- And if so, what parts of the NN would **you** act on?

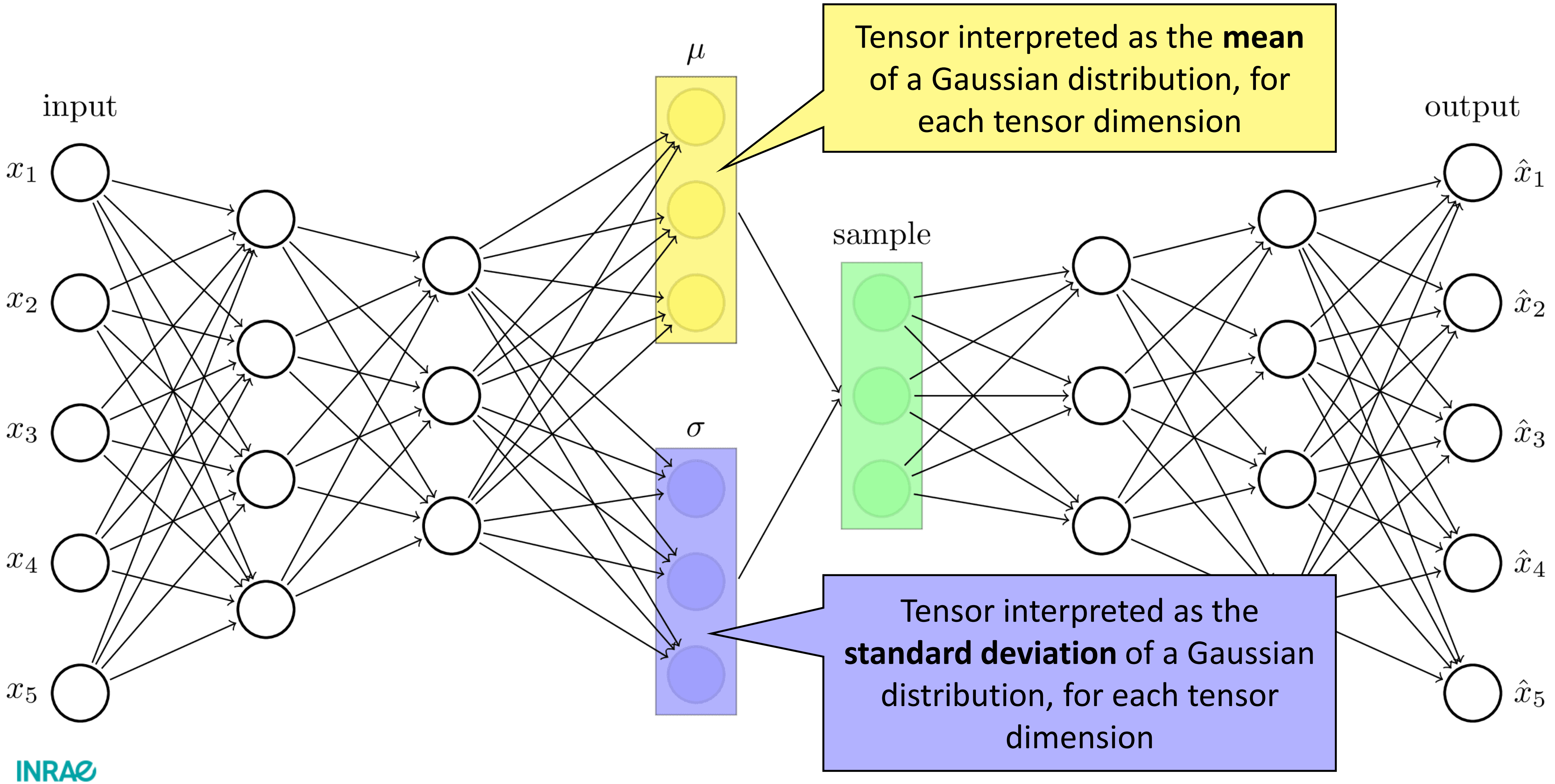
Variational Autoencoders

- Each image does **not** correspond to a single point
- But rather to a (Gaussian) distribution around a point
- This makes it possible to
  - Express *uncertainty* (small or large variance)
  - **Enforce structure** of the latent space (less brittle)

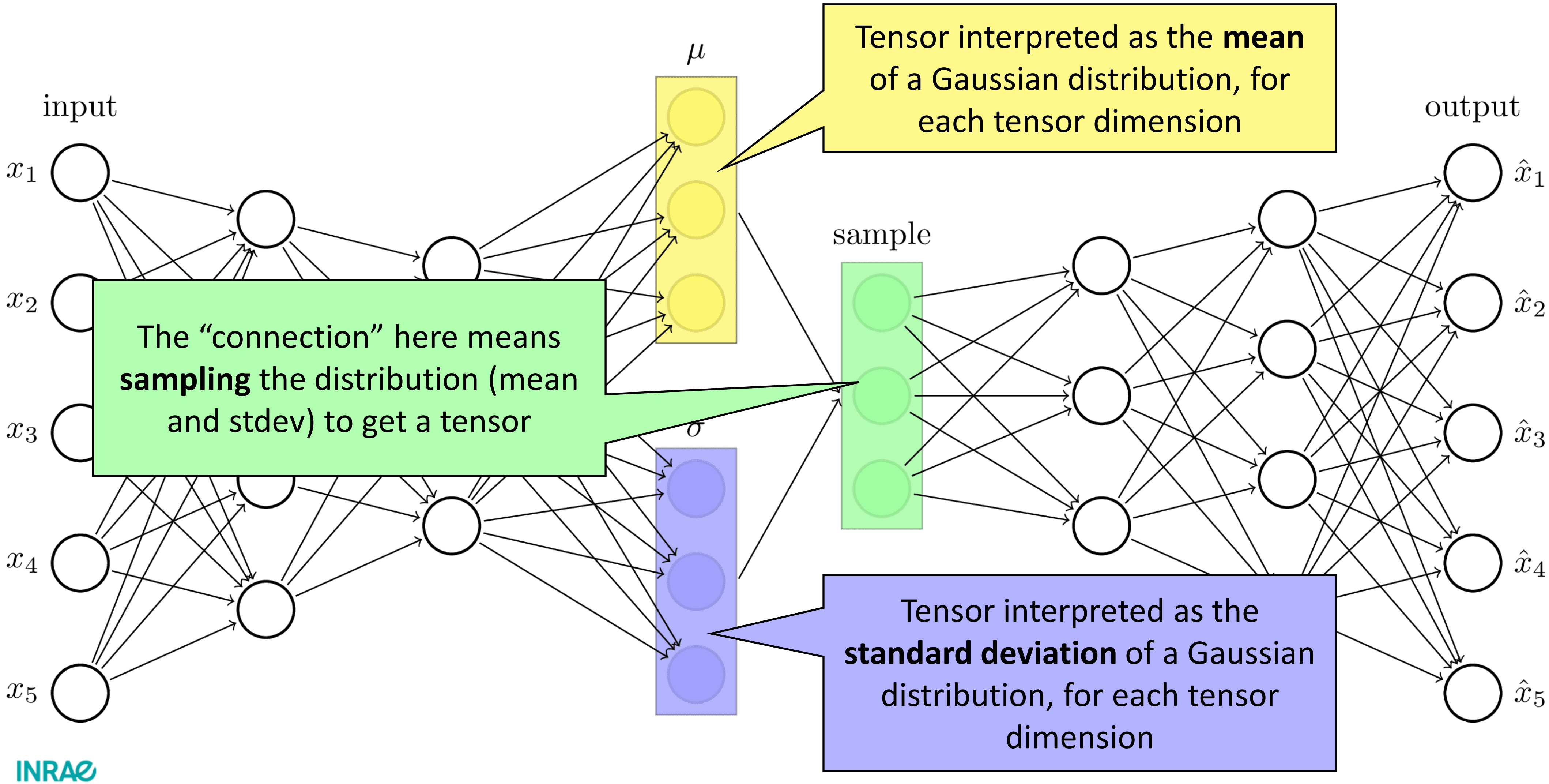
Variational Autoencoders



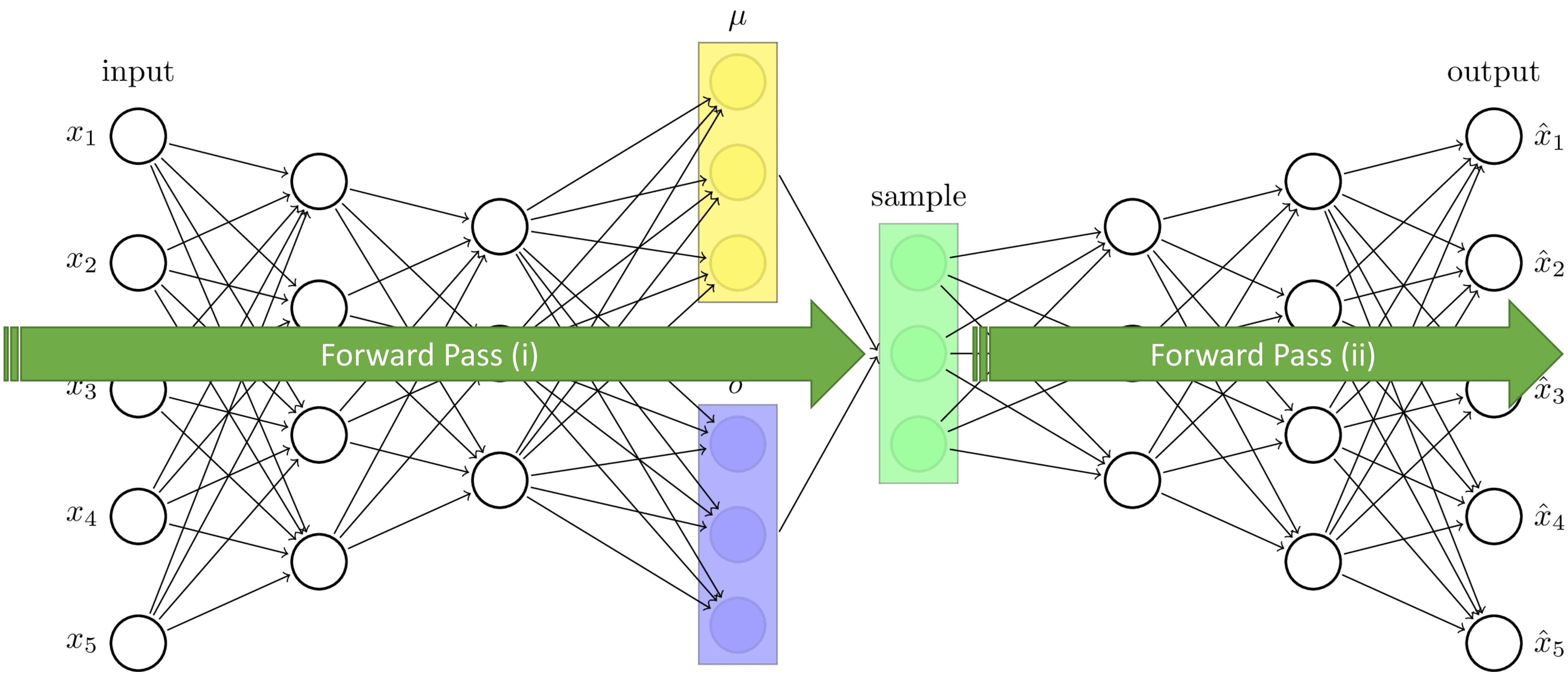
Variational Autoencoders



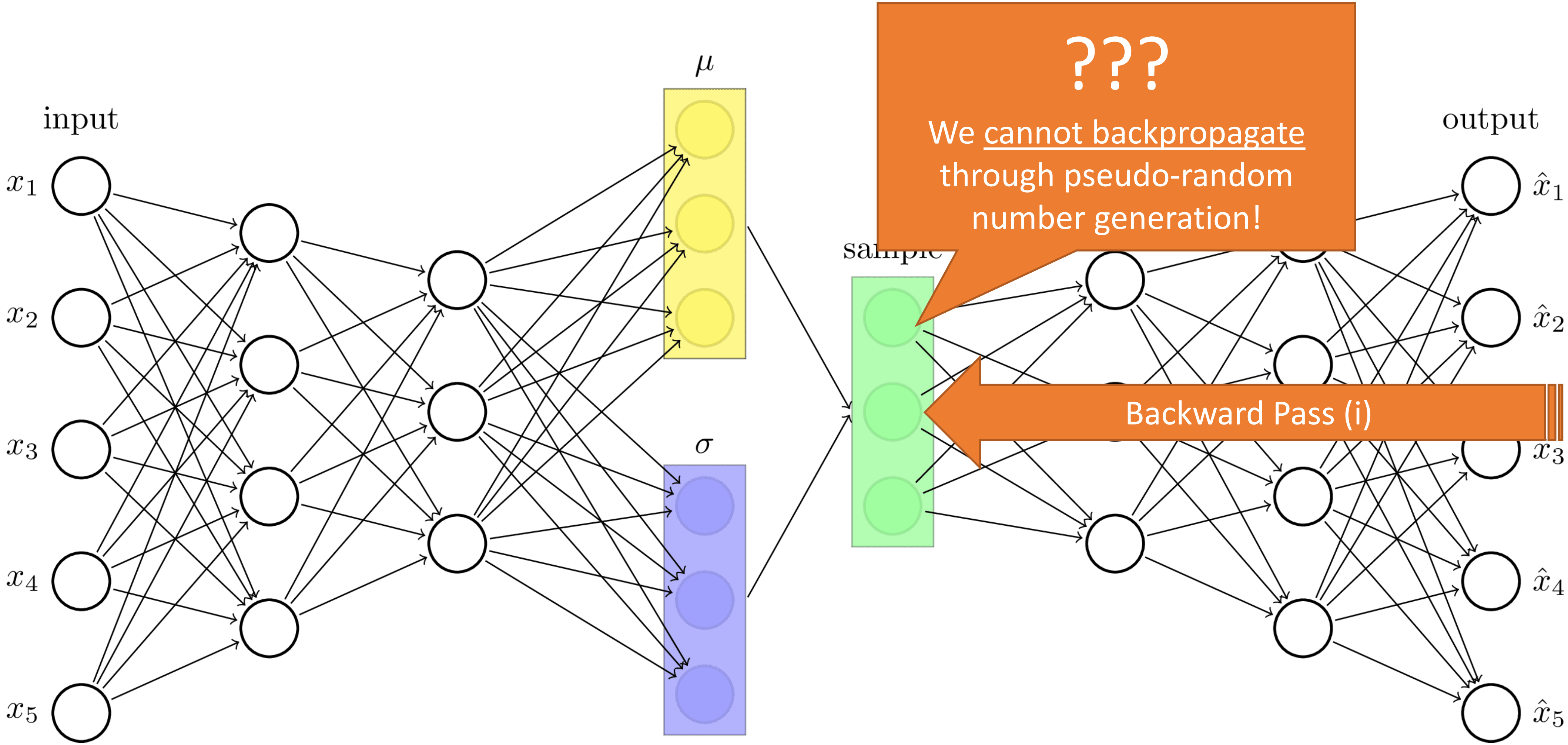
Variational Autoencoders



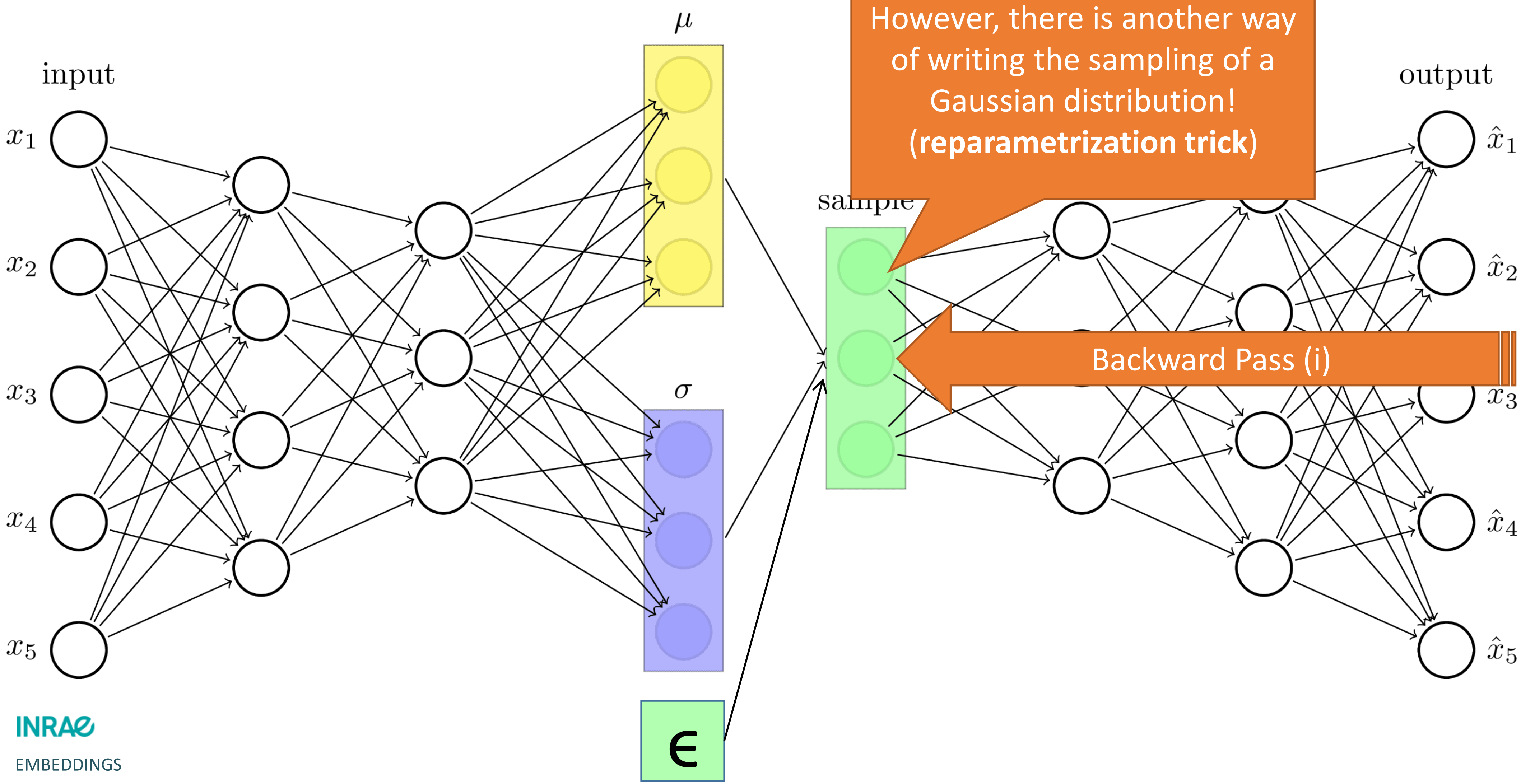
Variational Autoencoders



Variational Autoencoders

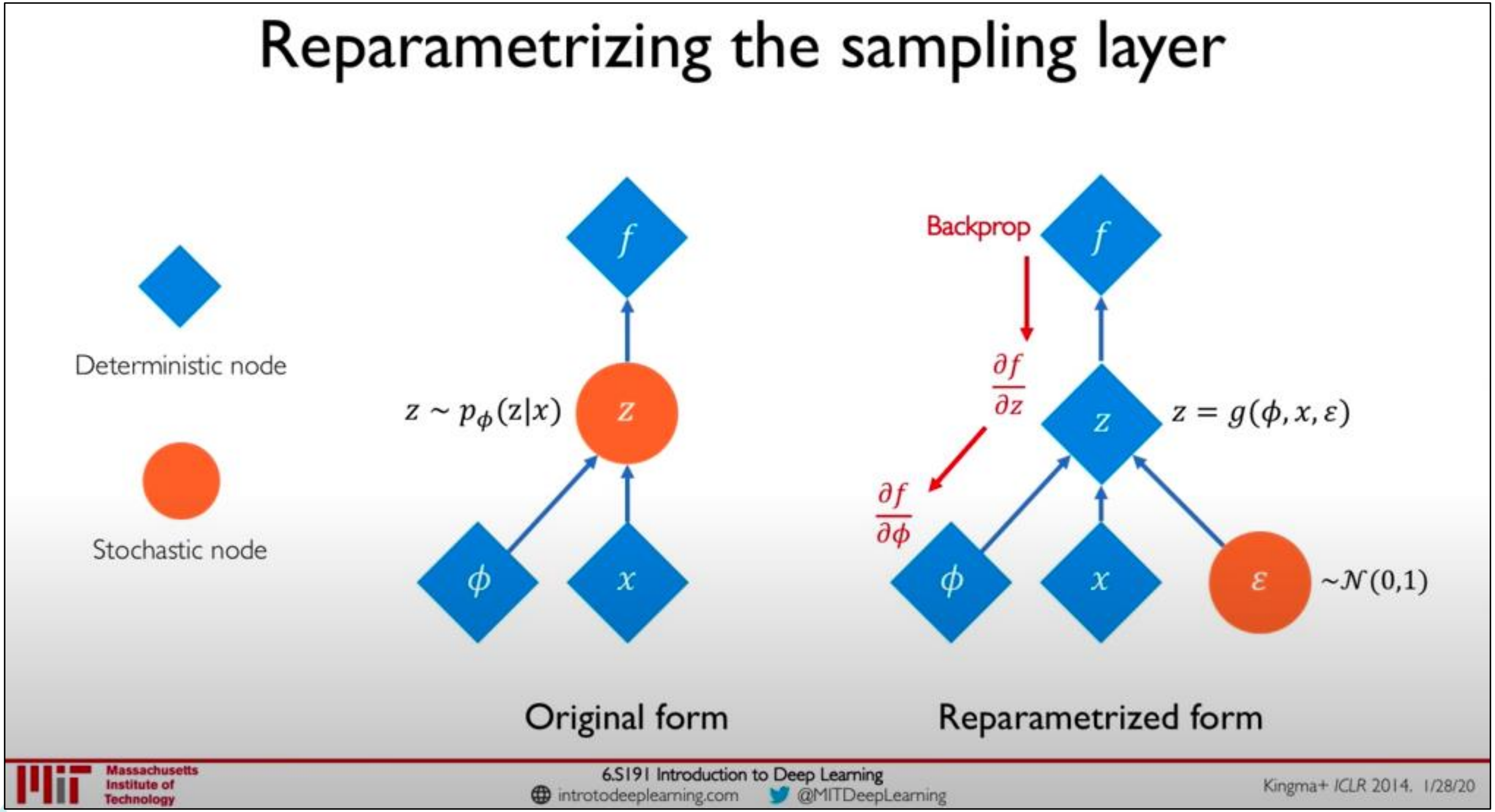


$$z \in \mathcal{N}(\mu, \sigma^2) \longrightarrow z = \mu + \sigma \odot \epsilon, \text{ where } \epsilon \in \mathcal{N}(0,1)$$

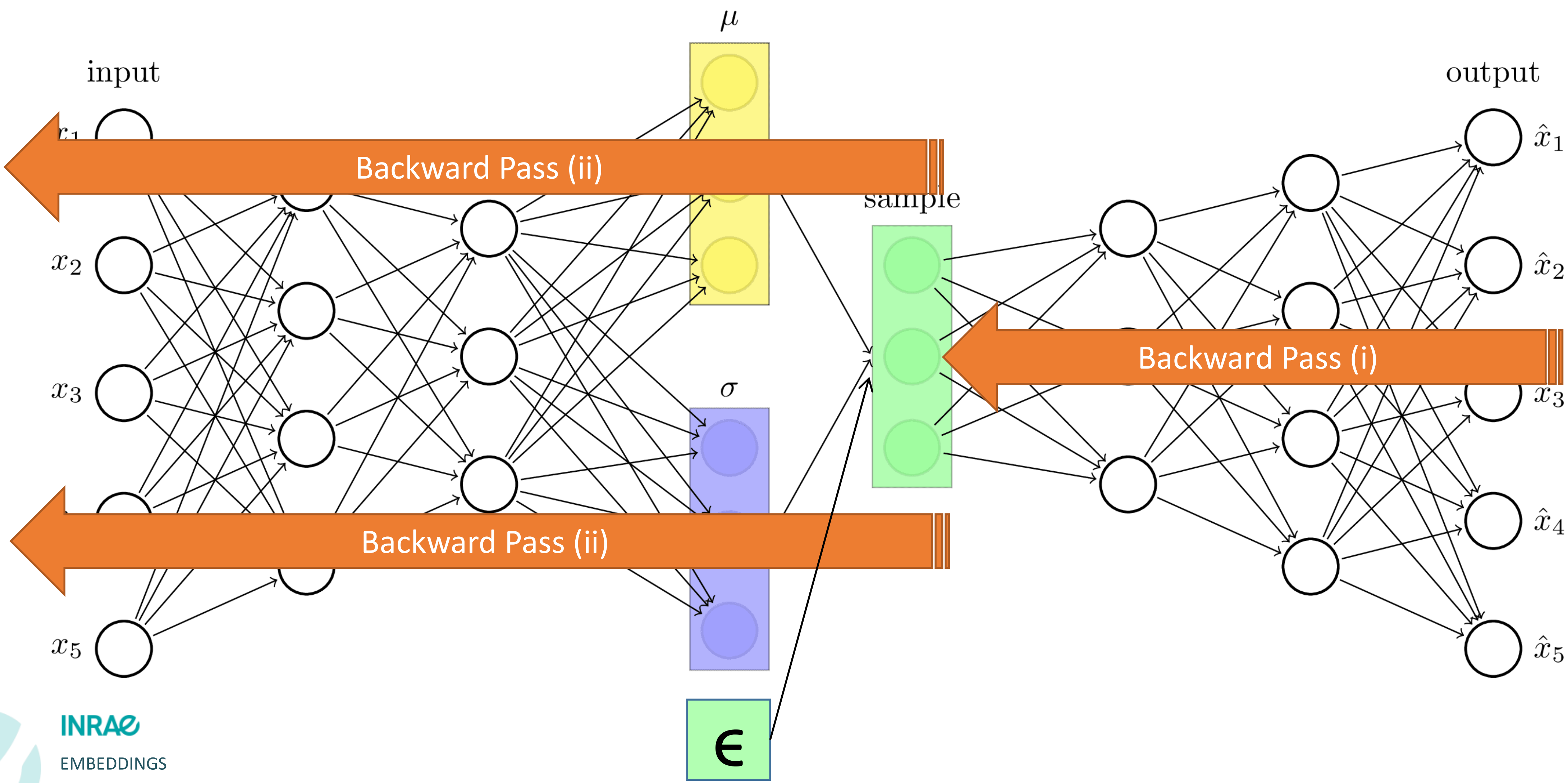


However, there is another way of writing the sampling of a Gaussian distribution! (**reparametrization trick**)

Variational Autoencoders



Variational Autoencoders



Variational Autoencoders

- Loss function in two parts
- The first one checks correctness of the output
  - For example, pixel-wise MSE or binary cross-entropy (BCE)
  - BCE assumes that pixels are "on" or "off" {0,1}
- The second one tries to keep distribution close to $\mathcal{N}(0, I)$
  - In other words, for each dimension Gaussian has $\mu = 0$
  - And covariance matrix is an identity matrix I
  - Which means that all latent dimensions are independent
- They can be weighted with a hyperparameter (β-VAE)

Variational Autoencoders

- Evaluating the difference between two distributions is hard
- Kullback–Leibler divergence

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log \frac{P(x)}{Q(x)}.$$

- However, if both distributions are Gaussians, becomes easier

Embeddings of Vocabularies

- Vocabulary
  - Set of finite size, discrete elements (element: “token”)
  - Classic example: words, characters, bitstrings
  - But also, e.g. possible chessboard configurations in chess

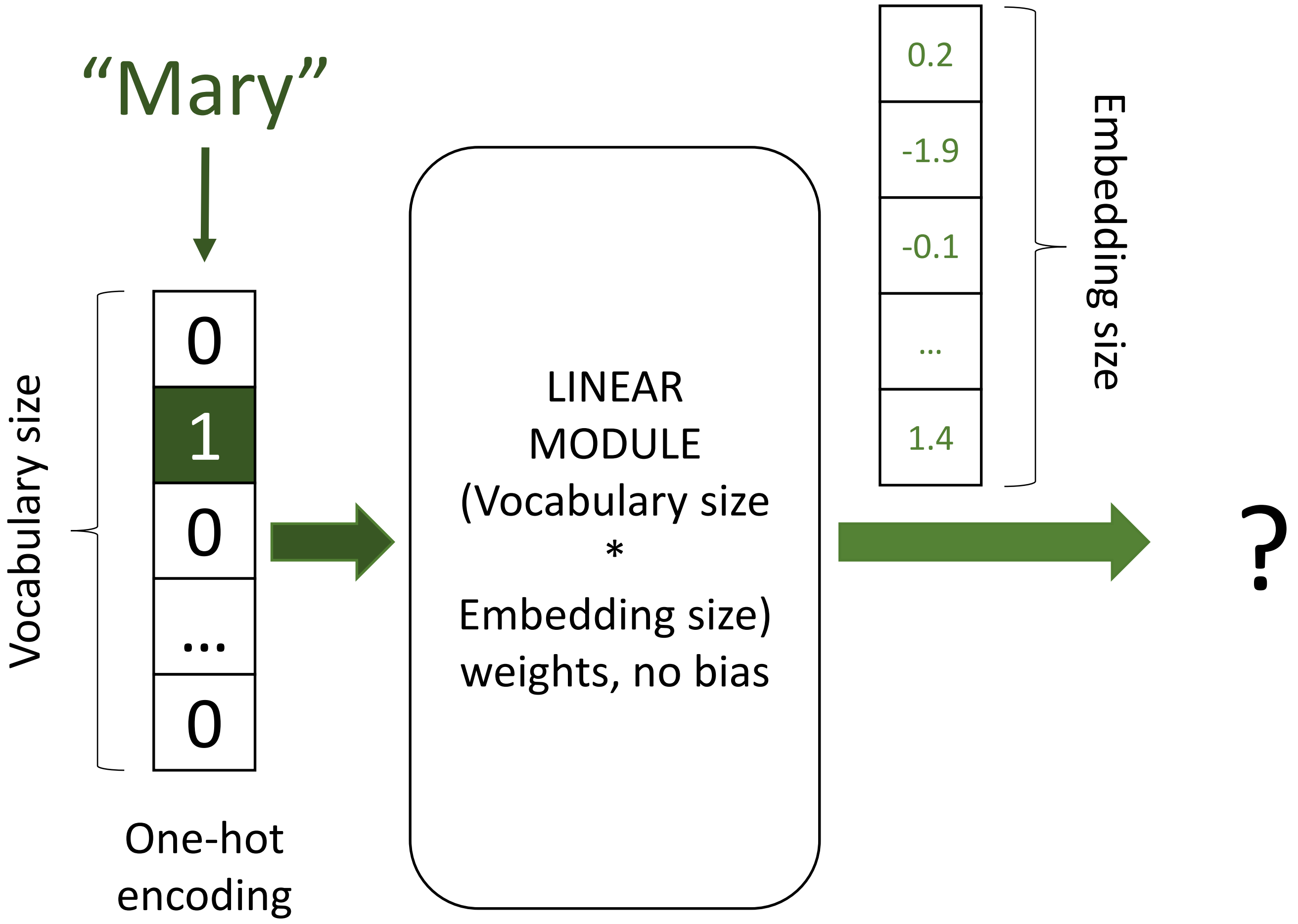
- **Words**, in particular, are difficult to manipulate for AI
  - Map to symbols, but not 1:1
  - “Chicken” vs “chicken”! “Mole” vs “mole” vs “mole”! *Context*?!?
  - Discrete: an integer per word? Not really expressive…

Vocabulary embedding: Word2Vec

- Revolutionary idea (grandfather of ChatGPT)
  - Arbitrary number of dimensions for the embedding
  - (n_vocabulary, n_embedding)

- Simple neural network architecture
  - Input: one-hot encoding of a vocabulary
  - Output/Loss: task connected to meaning
  - Use **learned weights** as **word embeddings**

Vocabulary embedding: Word2Vec



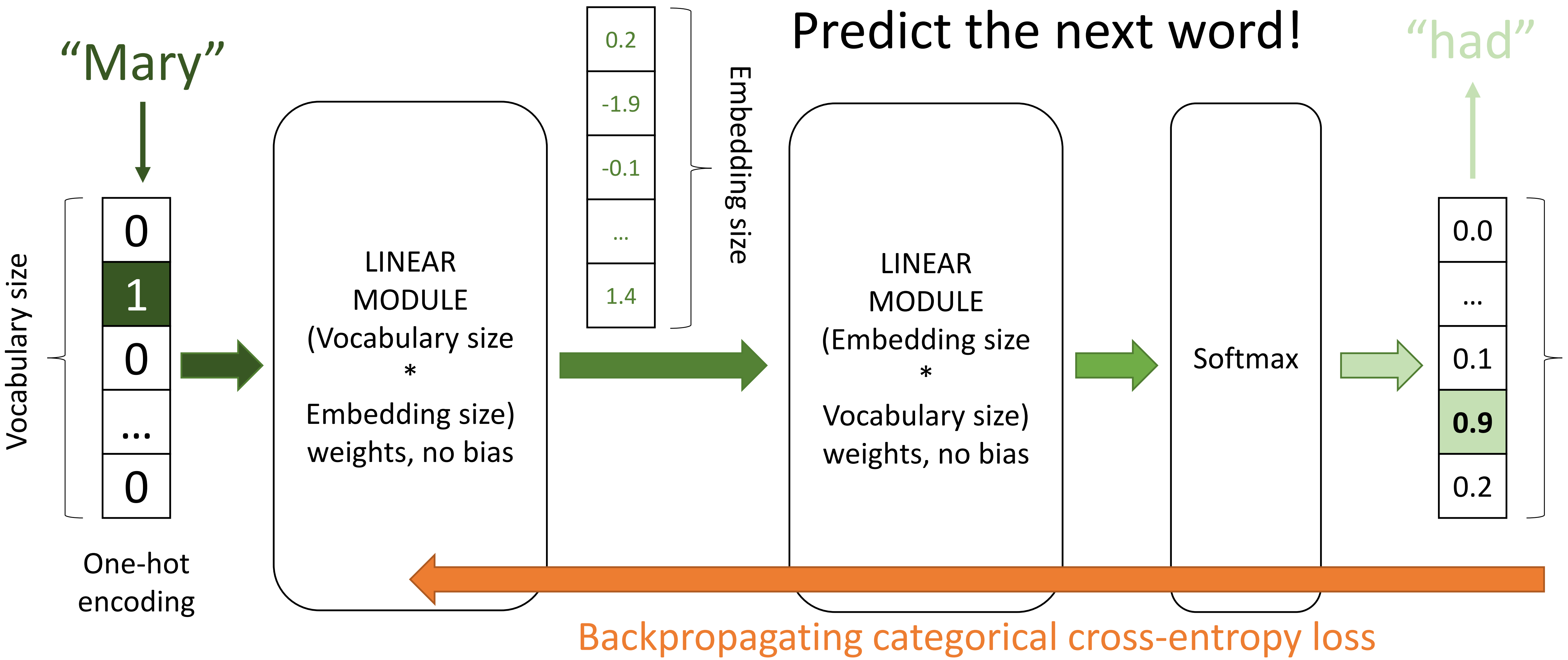
We don't have a task! How do we know if this representation is meaningful?

Vocabulary embedding: Word2Vec

- We already have lots of organized **relational data**
  - Text! Words are not randomly organized: sentences, paragraphs
  - Use text to generate meaningful training samples
  - Classic **unsupervised learning** tricks

- Slide a window on the text
  - For example, predict the next word
  - “Mary had a little lamb”
  - (Mary, had), (had, a), (a, little), (little, lamb)

Vocabulary embedding: Word2Vec



Vocabulary embeddings: Word2Vec

- Continuous Bag of Words (CBoW)
  - Predict the word between two other words
  - “Mary had a little lamb”
  - (Mary, had), (a, had); (had, a), (little, a); (a, little), (lamb, little)

Vocabulary embeddings: Word2Vec

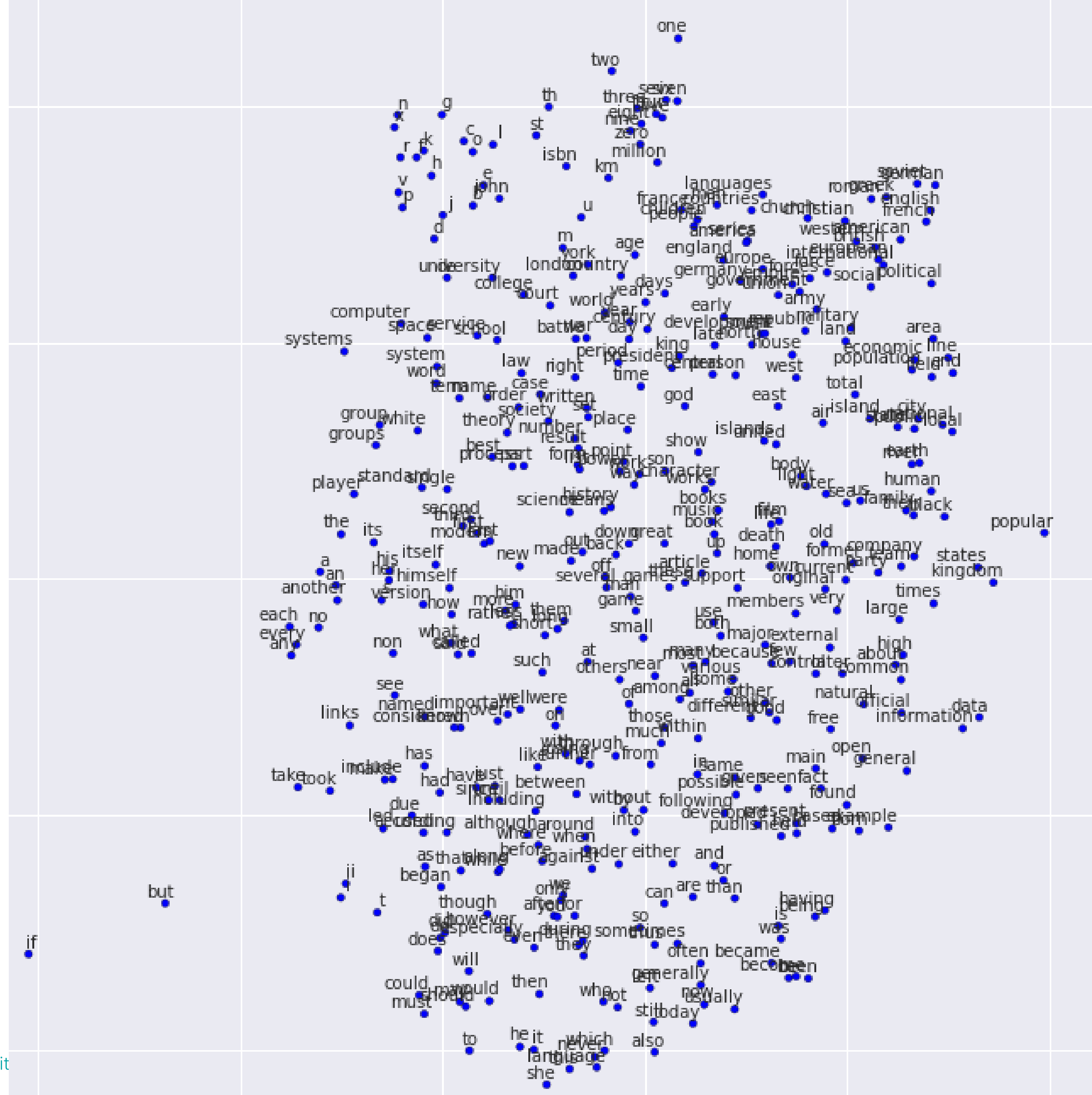
- Another possibility, skip-gram
  - "Context window" centered on a word, with n words on each side
  - Create training samples from central word to each side word

The [wide road **shimmered** in the] hot sun.

shimmered, wide
shimmered, road
shimmered, in
shimmered, the

- Skip-gram also uses **negative sampling**
  - For each positive sample (shimmered, wide)
  - Get *random words* that **don't appear** in context window
  - Loss function to get softmax outputs as close as possible to zero

Word2Vec



one
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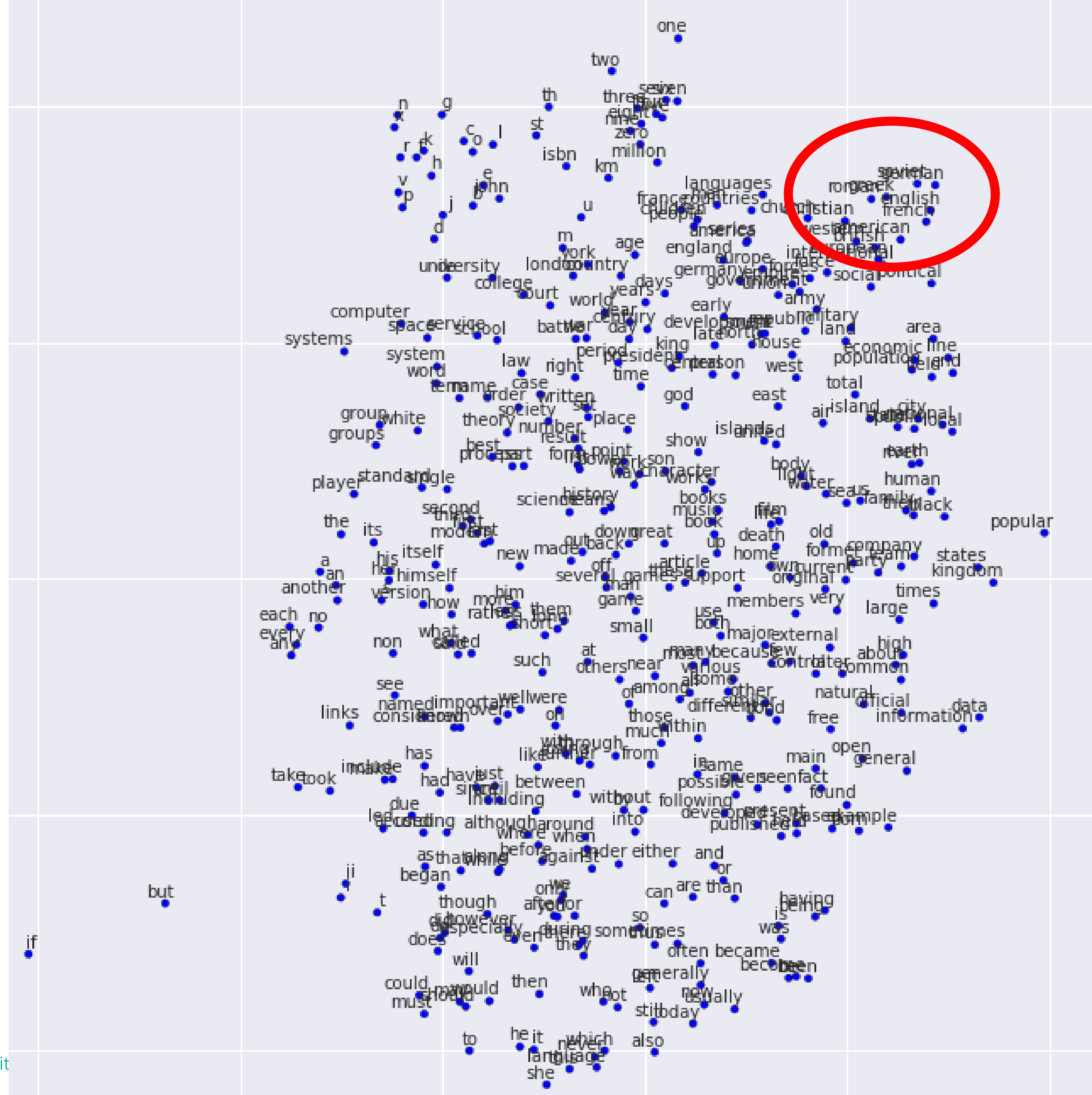
Word2Vec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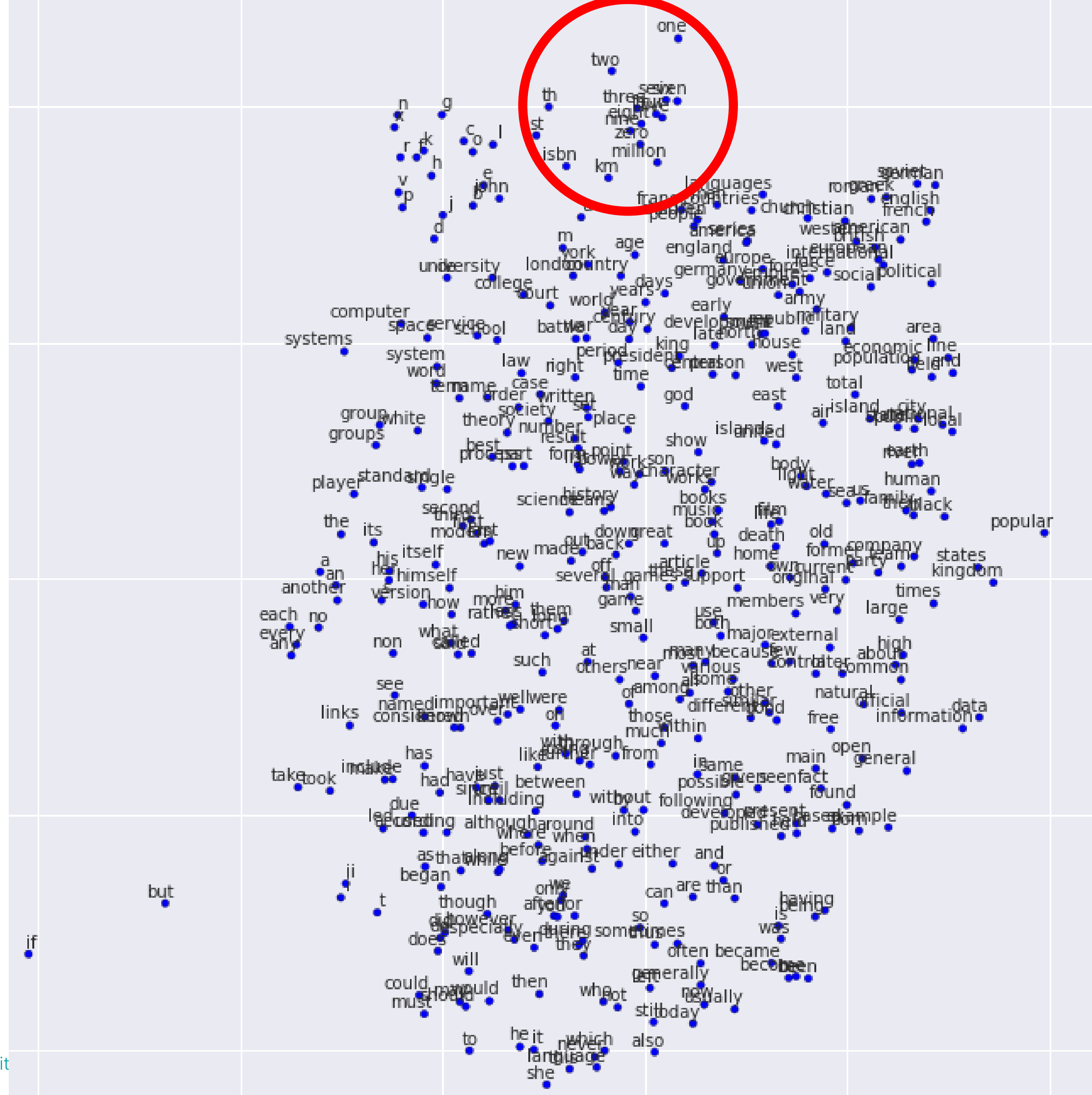
Word2Vec

- “French”, “British”, “American”…
  - Adjectives for nationality!
  - Nearby, you have “languages”, “countries”
  - Also, “England”, “Europe”, “International”, …

Word2Vec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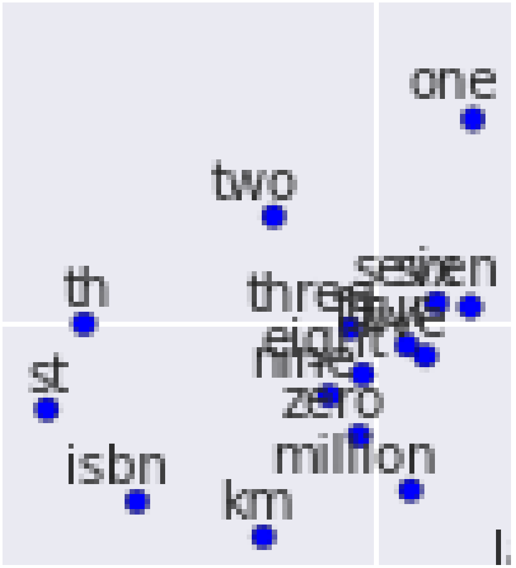
Word2Vec

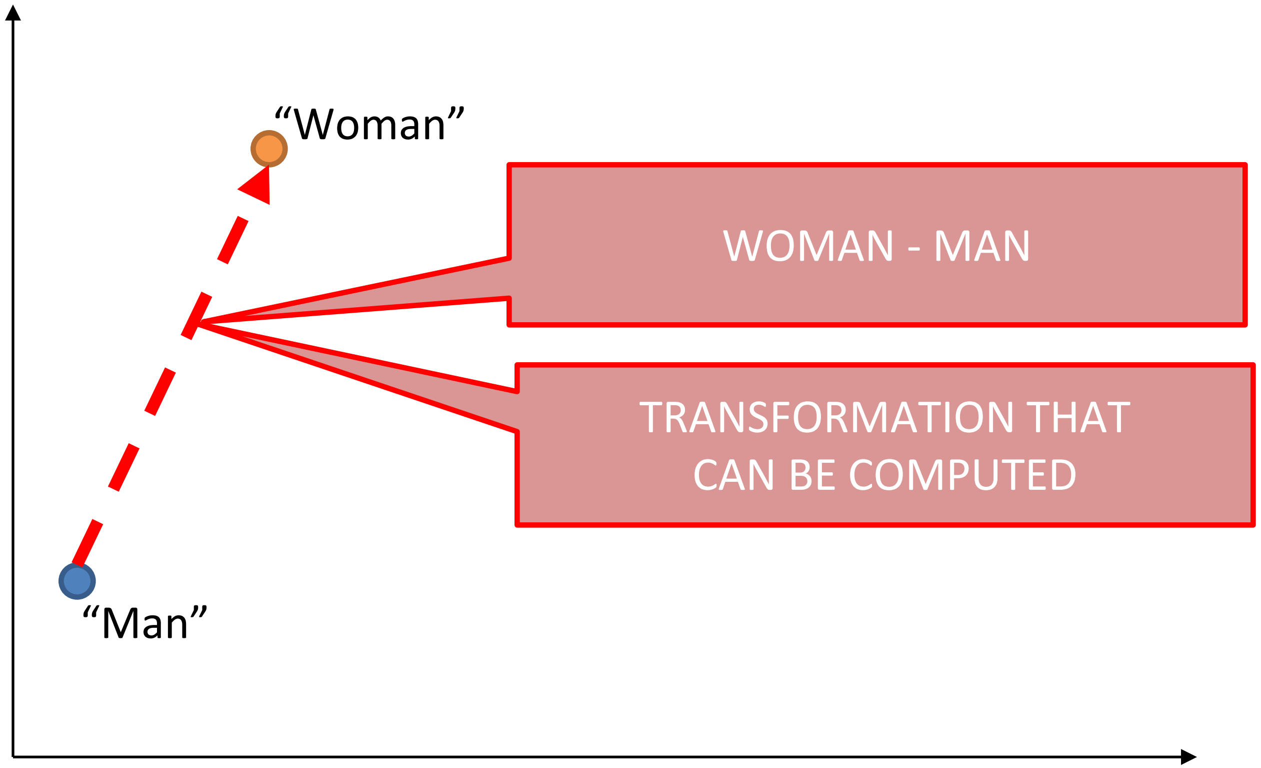


- “one”, “two”, “zero”, “seven”, “million”…
  - Numbers, quantities; nearby, some units of measurement
  - Also “th”, and “st”, as in 9-th, 1-st
  - ISBN (guess usually appears nearby numbers!)

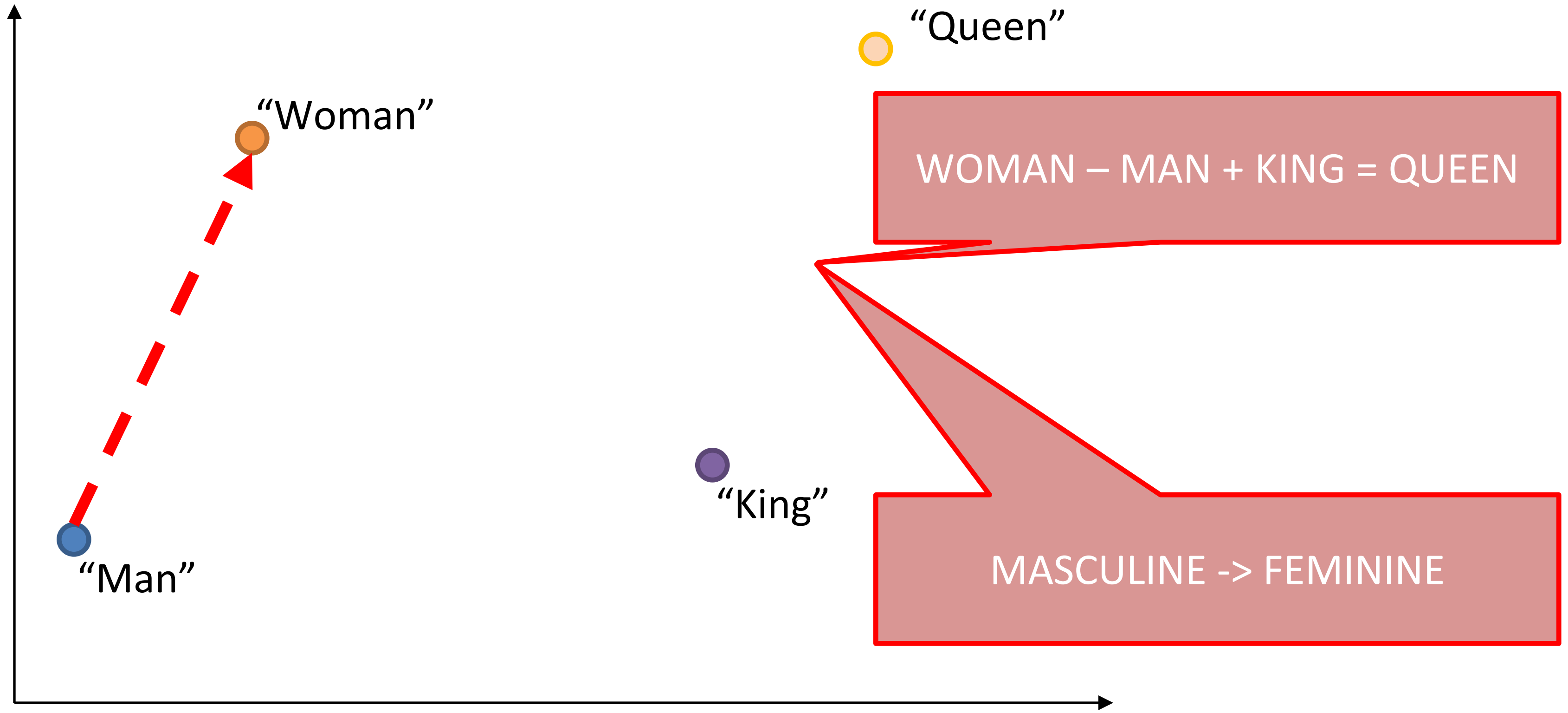
Word2Vec

- What is happening here?
  - Algorithm has **no semantic** info (**no meaning**)
  - But words with **similar meaning** are **close**
- Just by looking at the position of words in text
  - Similar *use* -> same *positions* with respect to other words
  - Word2Vec captures *some* aspects of meaning
- Can we do something else with Word2Vec?

Word2Vec

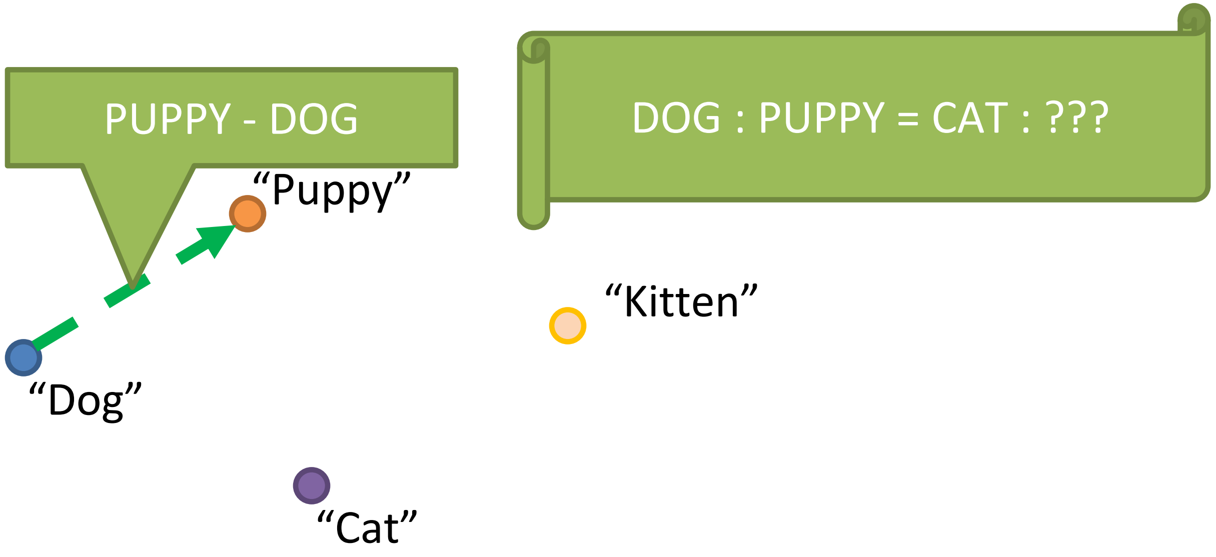


Word2Vec


"Queen"
"Woman"
WOMAN – MAN + KING = QUEEN
"King"
"Man"
MASCULINE -> FEMININE

Word2Vec

- Let's think about this for a second
  - No meaning inserted into the algorithm
  - Words with similar meaning cluster together
  - *Mathematical* transformations provide *meaningful* results



Word2Vec

- What does all this mean?
  - We are not really sure
  - Obtain *semantics* just from word positions
  - Maybe semantics is not as hard of a problem as it looks
- And Word2Vec is an incredibly *simple* architecture!
  - More complex architectures might get even better results
  - And they did (Transformers, ChatGPT, etc.)

Creating a Vocabulary

- Creating a Vocabulary is not straightforward
  - Elements in Vocabulary are called “tokens”
  - “Tokenization” is the process to create good tokens

- It’s another optimization problem
  - “What is the set of tokens that gives me the best result?”
  - E.g., discard or keep less frequent tokens?

Creating a Vocabulary

- Example: text from natural language?

Creating a Vocabulary

- Example: text from natural language?
- Seems pretty intuitive, 1 word = 1 token; but nuances
  - Special tokens, <SOS> (Start of Sequence) and <EOS> (End)
  - Actually more efficient to use **parts of a word**
    - “Cod” might be better than “Code”: “Cod-es”, “Cod-ing”, “En-cod-ing”
    - Kind like mapping to word roots, even if not exactly
- What happens if input is “**Grzegorz Brzęczyszczykiewicz**”?

Creating a Vocabulary

- In practice, solved by declaring **character-level tokens**
  - Tokenization attempts on largest possible matching tokens
  - If it fails, fall back on smaller and smaller tokens

- Test GPT-4 tokenization, platform.openai.com/tokenizer

Creating a Vocabulary

Questions?

Bibliography

- Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). *Efficient estimation of word representations in vector space*. arXiv preprint arXiv:1301.3781.