In [1]:
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%run Latex_macros.ipynb
```

References

- Triplet Loss: [FaceNet: A Unified Embedding for Face Recognition and Clustering (https://arxiv.org/pdf/1503.03832.pdf)](https://arxiv.org/pdf/1503.03832.pdf)
- Sentence BERT: [entence-BERT: Sentence Embeddings using Siamese BERT-Networks (https://arxiv.org/pdf/1908.10084.pdf)](https://arxiv.org/pdf/1908.10084.pdf))

Embeddings

We speculate that a Neural Network is creating an alternate representation of the input

- into a latent space that enables a Head Layer (e.g., Classifier) to do its work
- training the model produces a representation that has features useful to the Head to complete its task (e.g., Classification)

We will refer to these alternate representations as *embeddings*.

When we plot embeddings in the latent space

- we might hope to see clustering of examples that are related

For example, here is a plot of a subset of the 10 digits in a 2D latent space

And here is the clustering of text articles across different classes.

If such clusters were associated with class labels, the Classifier Head's job would be facilitated.

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Attribution: [https://joeddav.github.io/blog/2020/05/29/ZSL.html (https://joeddav.github.io/blog/2020/05/29/ZSL.html)](https://joeddav.github.io/blog/2020/05/29/ZSL.html)

We also hypothesize that

- that *intermediate* layers (distance greater than 1 from the Head) produ
  meaningful embeddings
- in Neural Style Transfer we hypothesized
  - the representation of shallow layers captures "syntax" (e.g. (
  - the representation of deeper layers captures "semantics" (e.

What does clustering enable ?

If a NN produced embeddings such that had the *desirable property* that

- the distance between the embeddings of related examples
- was *closer*
- than the distance between the embeddings of unrelated examples

what could we do ?

Zero-shot classification

Given an example and a set of possible labels

- using a pre-trained NN
- embed the example
- embed each of the labels

The label whose embedding was closest to that of the example would hope
correct label for the example.

This is *zero shot*

- since we are not fine-tuning
- or changing the weights
- of the pre-trained NN used to create the embeddings

Semantic search

Want to create your own search engine ?

- create embeddings (using a NN for NLP) for each document
- create an embedding for your query

A simple example: facial (or image) recognition

- compare the embedding of an image
- with the embeddings of the fixed number of images for each class (e.

The document whose embedding is closest to the query's embedding woul
the correct result.

Note

This is the basis for *Vector Stores*

- augmenting a LLM with your own data (e.g., GPT)

Creating embeddings for similarity

The problem is that the hoped-for desirable property *may not be true* withc
requiring that in training or fine-tuning.

We can train a Neural Network to have this property by

- creating a Loss function to express this objective

One such objective is the [Triplet Loss (https://arxiv.org/pdf/1503.03832.pd](https://arxiv.org/pdf/1503.03832.pdf)

Consider an input a (the "anchor")

Example: Sentence Embeddings

- with related input p ("positive")
- with unrelated input n ("negative")

To illustrate, we show [Sentence BERT (https://arxiv.org/pdf/1908.10084.p](https://arxiv.org/pdf/1908.10084.pdf)

Let

- fine-tunes the embeddings produced by BERT
- s_a, s_p, s_n be the embedding produced by some layer given input a,
- in order to make related sentences close in embedding space
- $||s - s'||$ be a measure of the distance (inverse of similarity, always
  between two embeddings s, s'

The Triplet Loss objective is to *minimize*

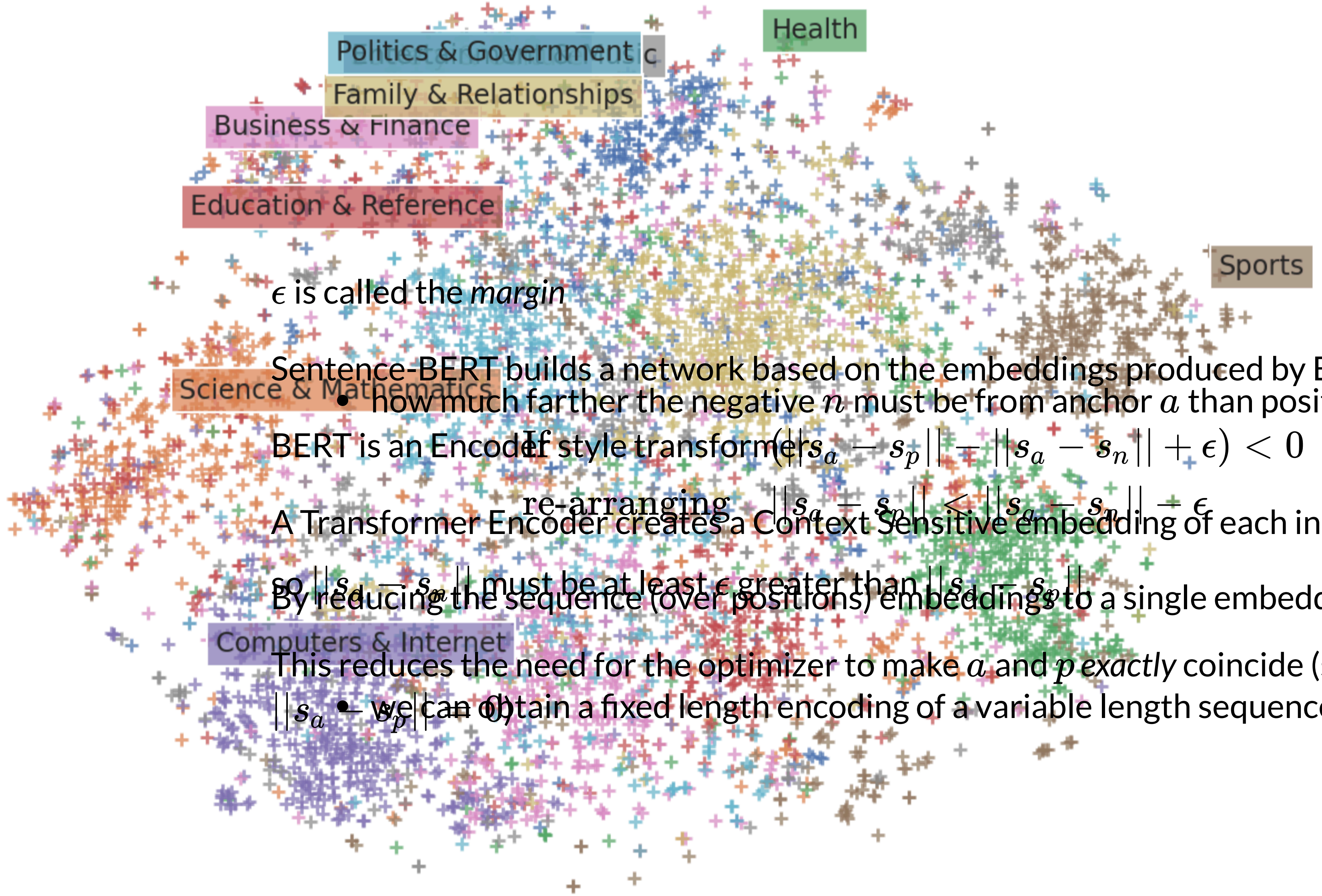
$$\max(||s_a - s_p|| - ||s_a - s_n|| + \epsilon, 0)$$

The loss is minimized when

- s_a is close to s_p
- s_a is far from s_n

That is the embedding for anchor

- a is very similar to that for p
- a is very dissimilar to that for n



ϵ is called the *margin*

- how much farther the negative n must be from anchor a than positiv

If $(||s_a - s_p|| - ||s_a - s_n|| + \epsilon) < 0$

re-arranging $||s_a - s_p|| < ||s_a - s_n|| + \epsilon$

so $||s_a - s_n||$ must be at least ϵ greater than $||s_a - s_p||$

This reduces the need for the optimizer to make a and p *exactly* coincide (so $||s_a - s_p|| = 0$)

Sentence-BERT builds a network based on the embeddings produced by BE

BERT is an Encoder style transformer

A Transformer Encoder creates a Context Sensitive embedding of each inpu

By reducing the sequence (over positions) embeddings to a single embeddi

- we can obtain a fixed length encoding of a variable length sequence o

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Attribution: [https://arxiv.org/pdf/1908.10084.pdf#page=3 (https://arxiv.org/pdf/1908.10084.pdf#page=3)](https://arxiv.org/pdf/1908.10084.pdf#page=3)

The pre-trained BERT model is *shared* across two inputs: Sentence A and Ser

- "weights are tied"
- BERT's weights are fine-tuned via the Triplet Loss objective

The sequence output of BERT is reduce by pooling (in this case)

By training (or fine-tuning a pre-trained model) with the Triplet Loss

- Sentence A is embedded as u
- Sentence B is embedded as v

we enforce the "holds-for" property by design

In the diagram on the right, the Triplet Objective

- is recast as maximizing similarity (cosine distance)
- rather than minimizing distance

Aside

Historically, there are some common ways to perform the reduction of a sec single value

- pooling (average over the embeddings)
- using a beginning/end "special" token (e.g., $\langle \mathrm{CLS} \rangle$ to capture the sur entire sequence

Aside

The diagram on the left is for producing embeddings for a specific task

- entailment
    - Does Sentence B logically follow from Sentence A
- and hence is expressed as a Classification objective over labels $\{\text{"Entail"}, \text{"Does not entail"}\}$

Here is the architecture

The inputs to the classifier are the concatenation of

- the embedding u of Sentence A
- the embedding v of Sentence B
- the difference in the embeddings

(Presumably these three inputs facilitate Classsification)

The model is trained via batches that contain a mixture of

- Positive examples: Sentence A and Sentence B *are related* (anchor a ar
- Negative examples: Sentence A and Sentence B *are un-related* (anchor positive n)

Triplet loss is minimized (or Utility maximized) in each batch.

Performance

[Here (https://github.com/UKPLab/sentence-transformers/blob/master/dc
models/sts-models.md#performance-comparison)] is a comparison of Sent
other methods

The Sentence Embedding (Universal Sentence Encoder) scores highest

- outperforms Word Embeddings (the two GloVe entries)
- it *greatly outperforms* the simple reduction methods used on plain BI
    - pooling (BERT as a service avg embeddings)
    - special <CLS> token (BERT as a service CLS vector)

Note

The "sophisticated" BERT, when using simple reduction methods

- underperforms the "old school" word embeddings !

In [6]:

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Done
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Sentence BERT