References

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

Embeddings

From our module on Transfer Learning (Transfer_Learning.ipynb) and CLIP (CLIP.ipynb)

- we understand that a Sequential Deep Learning model
- has multiple layers prior to the task-specific "head" (e.g., Classifier)
    - that create alternate representations of the Input
    - of increasing complexity as we go Deeper (closer to the Head)

The purpose of the layers from the Input to the Head

- is to create a representation
- from which the Head can correctly solve the task (e.g., predict the label)

These alternate representations are called *embeddings* of the Input.

We also hypothesize that

- embeddings that are close to the input
    - represent "syntax" concepts embeddings that are close to the Head
        - represent "semantic" concepts
        - but if we are too close to the Head
            - embeddings are over-specialized to the Source task used for training

We wish to understand behavior of embeddings visually.

Given a number of inputs

- we can compute the embedding of each
- and plot them in embedding space
- in order to understand the structure of embedding space

Here is a plot of the embeddings

- of a subset of the 10 digits

Although embeddings are typically high dimension

- we plot in 2D space
    - define by the first 2 Principal Components
- as a practical matter

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

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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)

It would seem

- that examples of the *same class* (e.g., digit or article topic)
- have embeddings that are close to one another
    - forming clusters in embedding space

This may explain why

- feeding embeddings into a Classifier head
- results in successful Classification

Using Embeddings to solve a task without fi

The traditional way that we have used Embeddings is via Transfer Learning

- keep a prefix of layers of a model trained for a Source task
    - use the embeddings created by the prefix
- append a new Head for a Target task
- train the Head on a small number of examples of the Target task
    - possibly also fine-tuning the weights in the prefix

Zero-shot classification

A simple approach to Classification via embeddings is like K-nearest neigh
But, we could use the embeddings directly

- map an input $\backslash\mathbf{x}$ to its embedding $\mathrm{embed}(\backslash\mathbf{x})$
- starting with a dataset of examples for a Target task
- create an equivalent dataset of embeddings
- predict $\backslash\hat{\mathbf{y}}$, the label of $\backslash\mathbf{x}$
    - map each input to its embedding
    - as the label $\backslash\mathbf{y}^{\backslash\mathrm{ip}}$ of an example $\langle \backslash\mathbf{x}^{\backslash\mathrm{ip}}, \backslash\mathbf{y}^{\backslash\mathrm{ip}} \rangle$
    - in a pre-defined set of labeled exampled

$$[\langle \backslash\mathbf{x}^{\backslash\mathrm{ip}}, \backslash\mathbf{y}^{\backslash\mathrm{ip}} \rangle \mid 1 \le i \le m]$$

- whose embedding $\mathrm{embed}(\backslash\mathbf{x}^{\backslash\mathrm{ip}})$
- is *closest* to $\mathrm{embed}(\backslash\mathbf{x})$

$$\mathrm{embed}(\backslash\mathbf{x}) \approx \mathrm{embed}(\backslash\mathbf{x}^{\backslash\mathrm{ip}})$$

- so predict $\backslash\hat{\mathbf{y}} = \backslash\mathbf{y}^{\backslash\mathrm{ip}}$

In this approach,

- we don't modify (or need access to the source code) the prefix layers
- just treat the Source model as producing embeddings

This is motivated by the possibility

- that a new Target task
- can be solved *without training*
- just by comparing embeddings

Semantic search

Want to create your own search engine ?

- create text embeddings for each document in a collection
- create an embedding of your query

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

Note that this approach

- does not involve computing/adapting parameters of any model
- zero-shot

Note

This is the basis for *Vector Stores*

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

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.g.

Creating embeddings for similarity

Using the similarity of embeddings to solve a new Target task

- assumes that
- the embedding or "related" inputs
- are close to one another

We may get lucky and this will be the case for many tasks.

But we may need to train our embeddings

- with this as the specific goal
- by adding this as an objective of the Loss function

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

Consider an input a (the "anchor")

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

Let

- s_a, s_p, s_n be the embedding produced by some layer, given input $a,$
- $||s - s'||$ be a measure of the distance (inverse of similarity, always r between two embeddings s, s'

Example: Sentence Embeddings

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

- fine-tunes the embeddings produced by BERT
- in order to make related sentences close in embedding space

The Triplet Loss objective is to *minimize*

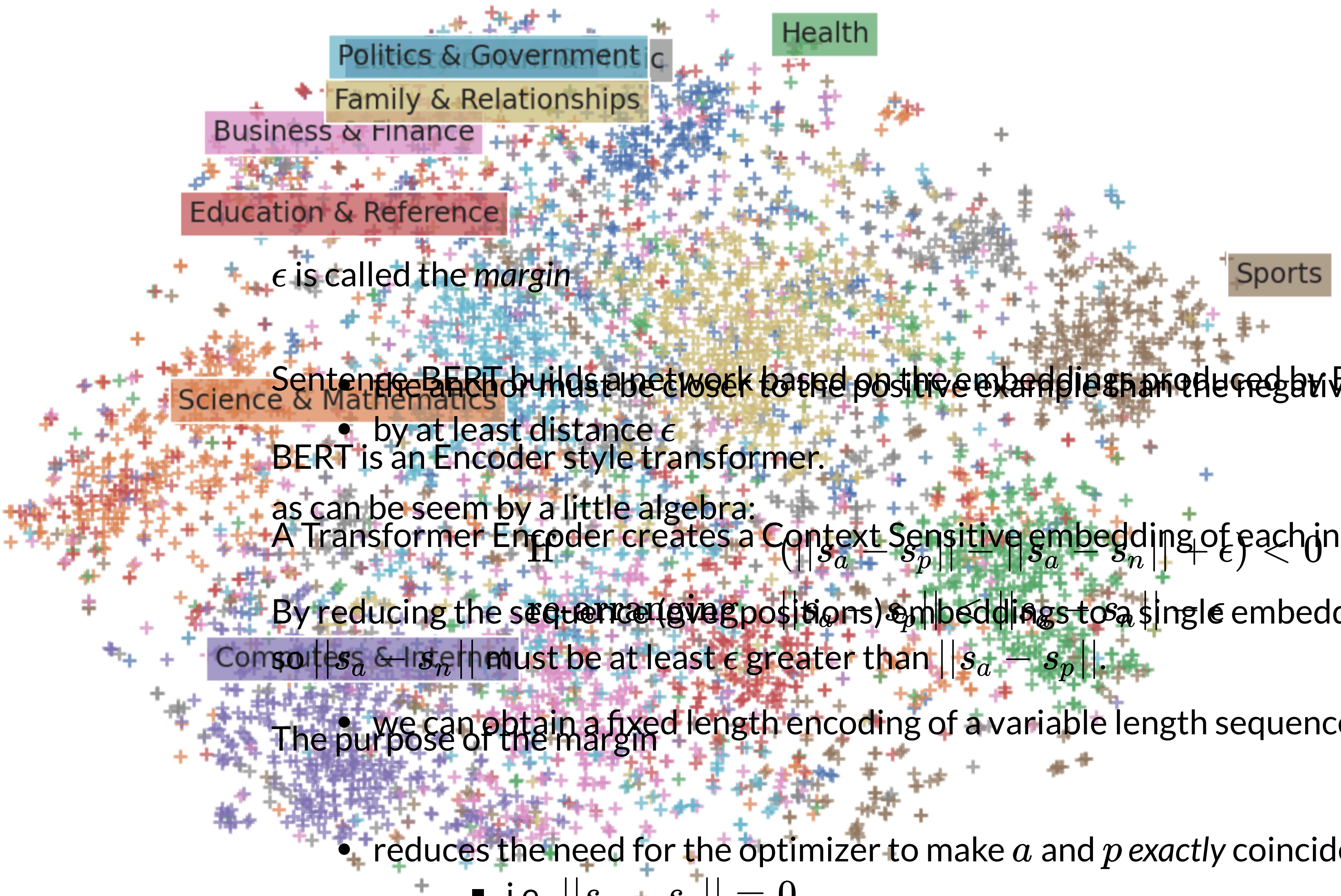
$$\max\left(||s_a - s_p|| - ||s_a - s_n|| + \epsilon, 0\right)$$

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*

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

- The anchor must be closer to the positive example than the negative
- by at least distance ϵ

BERT is an Encoder style transformer.

as can be seem by a little algebra:

A Transformer Encoder creates a Context Sensitive embedding of each inpu

$$\text{if} \quad (||s_a - s_p|| - ||s_a - s_n|| + \epsilon) < 0$$

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

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

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

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

The purpose of the margin

- reduces the need for the optimizer to make a and p *exactly* coincide
  - i.e., $||s_a - s_p|| = 0$

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Attribution: 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)

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

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., $\langle \text{CLS} \rangle$ to capture the sur entire sequence

Training a Source task with the Triplet Loss

- produces embeddings
- that are useful for tasks that compare similarity of embeddings

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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