Sentence Textual Similarity: Model Evolution Overview

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Outline

- Background and Preliminary
- Distance Measurement
- Model Evolution Overview
- Matrix-based Methods
- Alignment/Attention-based Methods
- Word Distance-based Methods
- Sentence Embedding-based Methods
- Evaluation Metrics
- Benchmark Databases
- Takeaways

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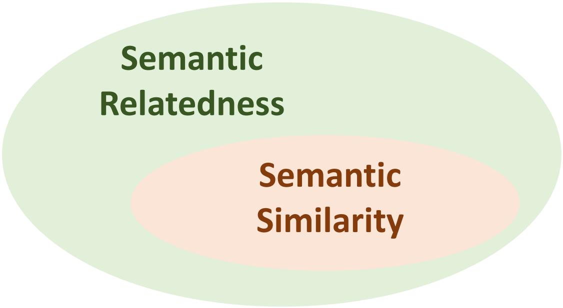
Part 1 – Background of *Semantic Textual Similarity (STS)*

- **What**: quantitatively measure of **semantic equivalence** between two blocks of texts, *i.e.*, sentences
- **How**: compute **semantic scores** between texts, measured by **semantic distance**
- **Intuition**: **rich interaction structures** in the text-matching process (words, phrases, whole sentences)
- **Challenge**: lack of large-scale **labeled** datasets (**sentence pairs** ⟺ **labeled semantic similarity scores**)
- **Semantic Relatedness** *vs.* **Semantic Similarity**:

  Broader perspective analyzing the shared semantic properties of two texts (*e.g.*, “coffee” and “mug”)



Credits: Chandrasekaran *et al.*, Evolution of Semantic Similarity—A Survey, In ACM Computing Survey’21.

Part 1 – Preliminary of *Word Embedding*

- **Bag-of-words Model (BoW)**: a model of text represented as an **unordered collection of words**, mainly used to **calculate frequencies of words** in different documents [1]
  - "John", "likes", "to", "watch", "movies", "Mary", "likes", "movies", "too"
  - BoW1 = {"John":1, "likes":2, "to":1, "watch":1, "movies":2, "Mary":1, "too":1}
- **Word Embedding**: **continuous vector representations** of words **that encode the meaning of the word** in such a way that words that are closer in the vector space are expected to be similar in meaning [2]
- **Distributional Hypothesis**: two words tend to be **semantically close** if they occur in **similar contexts** [3]
- **Word2Vec** [2]:
  - Continuously sliding bag-of-words (**CBOW**) – **Neighbor words** predict **center word**
  - Continuously sliding **skip-gram** – **Center word** predicts **neighbor words**

Credits: [1] Li *et al.*, Sentence Similarity Based on Semantic Nets and Corpus Statistics, In IEEE T-KDE'06.
[2] Mikolov *et al.*, Efficient Estimation of Word Representations in Vector Space, In ICLR'13. [3] Firth *et al.*, A Synopsis of Linguistic Theory, In Studies in Linguistic Analysis'1930.

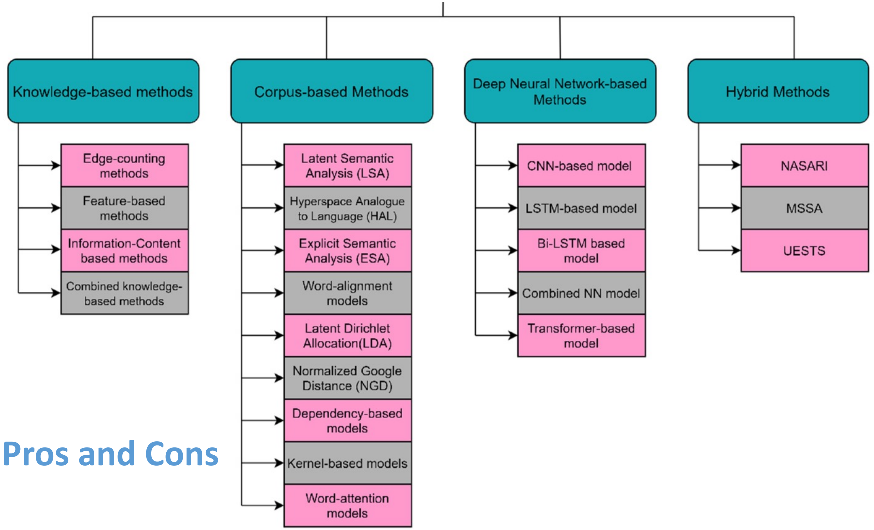
Part 1 — Preliminary of *Word Embedding*

- **FastText**: **average of character n-grams**, can provide embeddings for Out-of-vocabulary (OOV) words [1]
  - "equal" ← "eq", "equ", "qua", "ual", "al"
- **GloVe**: **word-word co-occurrences** within context windows ⟹ **ratios of co-occurrence probabilities** [2]
  - $P_{ij} = P(i|j) = X_{ij} / \sum_k X_{ik} \Longrightarrow$ the probability that word j appear in the context of word i
- **Skip-Thought Embeddings**: **Center sentence** predicts **neighbor sentences** [3]
- **Autoencoder BERT Embeddings**: **Masked Language Modeling** and **Next Sentence Prediction** [4]
  - "[CLS] The man went to the store. [SEP] He bought a gallon of milk."
- **Universal Sentence Encoder**: **sentence embedding** by **element-wise sum** and **length normalization** [5]

Credits: [1] Bojanowski *et al.*, Enriching Word Vectors with Subword Information, In TACL'17.
[2] Pennington *et al.*, GloVe: Global Vectors for Word Representation, In EMNLP'14.
[3] Kiros *et al.*, Skip-Thought Vectors, In NeurIPS'15.
[4] Devlin *et al.*, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, In NAACL'19.
[5] Cer *et al.*, Universal Sentence Encoder, In arXiv'18.

Part 1 – Preliminary of *Knowledge and Statistics Methods*

- **Faced with an *embarras de richesse***
- Bag-of-words Model (BoW) [1]
- Term Frequency-Inverse Document Frequency (TF-IDF) [2,3]
- Latent Semantic Indexing (LSI) [4]
- Latent Dirichlet Allocation (LDA) [5]
- **Traditional Works** mostly focus on **Word Similarity** [6]
- **Please check [6] to know more about Previous Works** and **Pros and Cons**



Credits:
[1] Li *et al.*, Sentence Similarity Based on Semantic Nets and Corpus Statistics, In IEEE T-KDE'06.
[2] Luhn *et al.*, A Statistical Approach to Mechanized Encoding and Searching of Literary Information, In IBM Journal of Research and Development'1957.
[3] Jones *et al.*, A Statistical Interpretation of Term Specificity and its Application in Retrieval, In Document Retrieval Systems'1988.
[4] Deerwester *et al.*, Indexing by Latent Semantic Analysis, In Journal of the American Society for Information Science'1990.
[5] Blei *et al.*, Latent Dirichlet Allocation, In JMLR'03.
[6] Chandrasekaran *et al.*, Evolution of Semantic Similarity—A Survey, In ACM Computing Survey'21.

Part 1 – Preliminary of *Baseline*

- **Avg. GloVe Embeddings**: average of GloVe embeddings [1]
- **Avg. Skip-Thought Embeddings**: average of word embeddings produced by Skip-Thought vectors [2]
- **InferSent**: a Siamese BiLSTM network with max-pooling over the output on NLI datasets [3]
- **Avg. BERT Embeddings**: average of word embeddings produced by BERT [4]
- **BERT [CLS]**: scores based on the vector representation of the special token [CLS] in BERT [4]
- **BERTScore**: the similarity of sentences as a sum of cosine similarities between tokens' embeddings [5]
- **BLEURT**: based on BERT and captures similarities by fine-tuning the model [6]
- **DPR**: two unique BERT encoders and the model weights are optimized to maximize the dot product [7]
- **Universal Sentence Encoder**: encoding sentences into their corresponding embeddings [8]
- **Sentence-BERT**: BERT + Siamese structure to derive sentence embeddings + compared through cosine similarity [9]

Credits: [1] Pennington *et al.*, GloVe: Global Vectors for Word Representation, In EMNLP'14. [2] Kiros *et al.*, Skip-Thought Vectors, In TACL'22.
[3] Conneau *et al.*, Supervised Learning of Universal Sentence Representations from Natural Language Inference Data, In EMNLP'17.
[4] Devlin *et al.*, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, In NAACL'19.
[5] Zhang *et al.*, BERTScore: Evaluating Text Generation with BERT, In ICLR'20. [6] Sellam *et al.*, BLEURT: Learning Robust Metrics for Text Generation, In ACL'20.
[7] Karpukhin *et al.*, Dense Passage Retrieval for Open-Domain Question Answering, In EMNLP'20.
[8] Cer *et al.*, Universal Sentence Encoder, In arXiv'18. [9] Reimers *et al.*, Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks, In EMNLP'19.

Part 2 – Distance Measurement – *Spatial Metrics*

- **Cosine Similarity** – words co-occur → small angle → large cosine

$$\mathrm{Cos}(w_1, w_2) = \frac{\sum_{w \in C(w_1) \cup C(w_2)} P(w|w_1) \times P(w|w_2)}{\sqrt{\sum_{w \in C(w_1)} P(w|w_1)^2} \times \sqrt{\sum_{C(w_2)} P(w|w_2)^2}}.$$

- **Manhattan Distance** or L_1 **Norm**

$$\mathrm{L}_1(w_1, w_2) = \sum_{w \in C(w_1) \cup C(w_2)} |P(w|w_1) - P(w|w_2)|.$$

- **Euclidean Distance** or L_2 **Norm**

$$\mathrm{L}_2(w_1, w_2) = \sqrt{\sum_{w \in C(w_1) \cup C(w_2)} \left(P(w|w_1) - P(w|w_2)\right)^2}.$$

Semantic distance: a measure of how close or distant the meanings of two units of language are.

Notions:

$C(w)$: the set of words that co-occur (within a certain window) with the word w in a corpus

$P(w|w_1)$: conditional probability of the co-occurring words given the target words is used as the strength of association

Credits: Mohammad *et al.*, Distributional Measures of Semantic Distance: A Survey, In arXiv'12.

Part 2 – Distance Measurement – *Mutual Information*

- **Hindle**

$$\mathrm{Hin}(w_1, w_2) = \sum_{w \in C(w)} \begin{cases} \min\big(I(w, w_1), I(w, w_2)\big), & \text{if both } I(w, w_1) \text{ and } I(w, w_2) \; > \; 0; \\ \left|\max\big(I(w, w_1), I(w, w_2)\big)\right|, & \text{if both } I(w, w_1) \text{ and } I(w, w_2) \; < \; 0; \\ 0, & \text{otherwise.} \end{cases}$$

$I(w_1, w_2)$ is the Pointwise Mutual Information (PMI) between w_1 and w_2. Using the minimum of the two PMIs captures the similarity of the occurred words w and two words w_1 and w_2.

- **Lin**

$$\mathrm{Lin}(w_1, w_2) = \frac{\sum_{(r,w) \in T(w_1) \cap T(w_2)} \big(I(w_1, r, w) + I(w_2, r, w)\big)}{\sum_{(r,w') \in T(w_1)} \big(I(w_1, r, w')\big) + \sum_{(r,w'') \in T(w_2)} \big(I(w_2, r, w'')\big)},$$

where the word w_1 is related to w by the syntactic relation r, and $T(w_1)$ is the set of all word pairs (r, w) such as pos. I.

Credits: Mohammad *et al.*, Distributional Measures of Semantic Distance: A Survey, In arXiv'12.

Part 2 — Distance Measurement — *Relative Entropy*

- **Kullback-Leibler Divergence/Distance (KLD)/Relative Entropy — Common Occurrence**

$$\mathrm{KLD}(w_1, w_2) = D\big(P(w|w_1)||P(w|w_2)\big) = \sum_{w \in C(w_1) \cup C(w_2)} P(w|w_1) \log \frac{P(w|w_1)}{P(w|w_2)}.$$

The more $P(w|w_1)$ and $P(w|w_2)$ are similar, the more w_1 and w_2 are semantically similar.

- **Kullback-Leibler Divergence (KLD) — Absolute**

$$\sum_{w \in C(w_1) \cup C(w_2)} P(w|w_1) \left| \log \frac{P(w|w_1)}{P(w|w_2)} \right|.$$

- **Kullback-Leibler Divergence (KLD) — Average**

$$\frac{1}{2} \sum_{w \in C(w_1) \cup C(w_2)} \big(P(w|w_1) - P(w|w_2)\big) \log \frac{P(w|w_1)}{P(w|w_2)}.$$

- **Kullback-Leibler Divergence (KLD) — Maximum**

$$\max\big(\mathrm{KLD}(w_1, w_2), \mathrm{KLD}(w_2, w_1)\big).$$

Credits: Mohammad *et al.*, Distributional Measures of Semantic Distance: A Survey, In arXiv'12.

Part 2 – Distance Measurement – *Relative Entropy*

- **α-skew Divergence (ASD)**

  A slight modification of the KLD that obviates the need for smoothed probabilities

$$\mathrm{ASD}(w_1, w_2) = \sum_{w \in C(w_1) \cup C(w_2)} P(w|w_1) \log \frac{P(w|w_1)}{\alpha P(w|w_2) + (1-\alpha) P(w|w_1)},$$

where α is usually set to 0.99. Better estimate word co-occurrence probabilities than KLD.

- **Jensen-Shannon Divergence (JSD)/total divergence to the average/information radius**

  A relative entropy–based measure that overcomes the problem of asymmetry in KLD

$$\mathrm{JSD}(w_1, w_2) = \sum\nolimits_{w \in C(w_1) \cup C(w_2)} \left(P(w|w_1) \log \frac{P(w|w_1)}{\frac{1}{2}\big(P(w|w_1) + P(w|w_2)\big)} + P(w|w_2) \log \frac{P(w|w_2)}{\frac{1}{2}\big(P(w|w_1) + P(w|w_2)\big)} \right).$$

Credits: Mohammad *et al.*, Distributional Measures of Semantic Distance: A Survey, In arXiv'12.

Part 2 — Distance Measurement

- **Co-occurrence Retrieval Models (CRM)**

$$\mathrm{CRM}(w_1, w_2) = \gamma\left[\frac{2\times P\times R}{P+R}\right] + (1-\gamma)\big[\beta[P] + (1-\beta)[R]\big].$$

- **Dice Coefficient**

$$\mathrm{Dice}(w_1, w_2) = \frac{2\times \sum_{w\in C(w_1)\cup C(w_2)} \min\big(P(w|w_1), P(w|w_2)\big)}{\sum_{w\in C(w_1)} P(w|w_1) + \sum_{w\in C(w_2)} P(w|w_2)}.$$

- **Division Measure**

$$\mathrm{Division}(w_1, w_2) = \sum_{w\in C(w_1)\cup C(w_2)} \left|\log\frac{P(w|w_1)}{P(w|w_2)}\right|.$$

- **Jaccard**

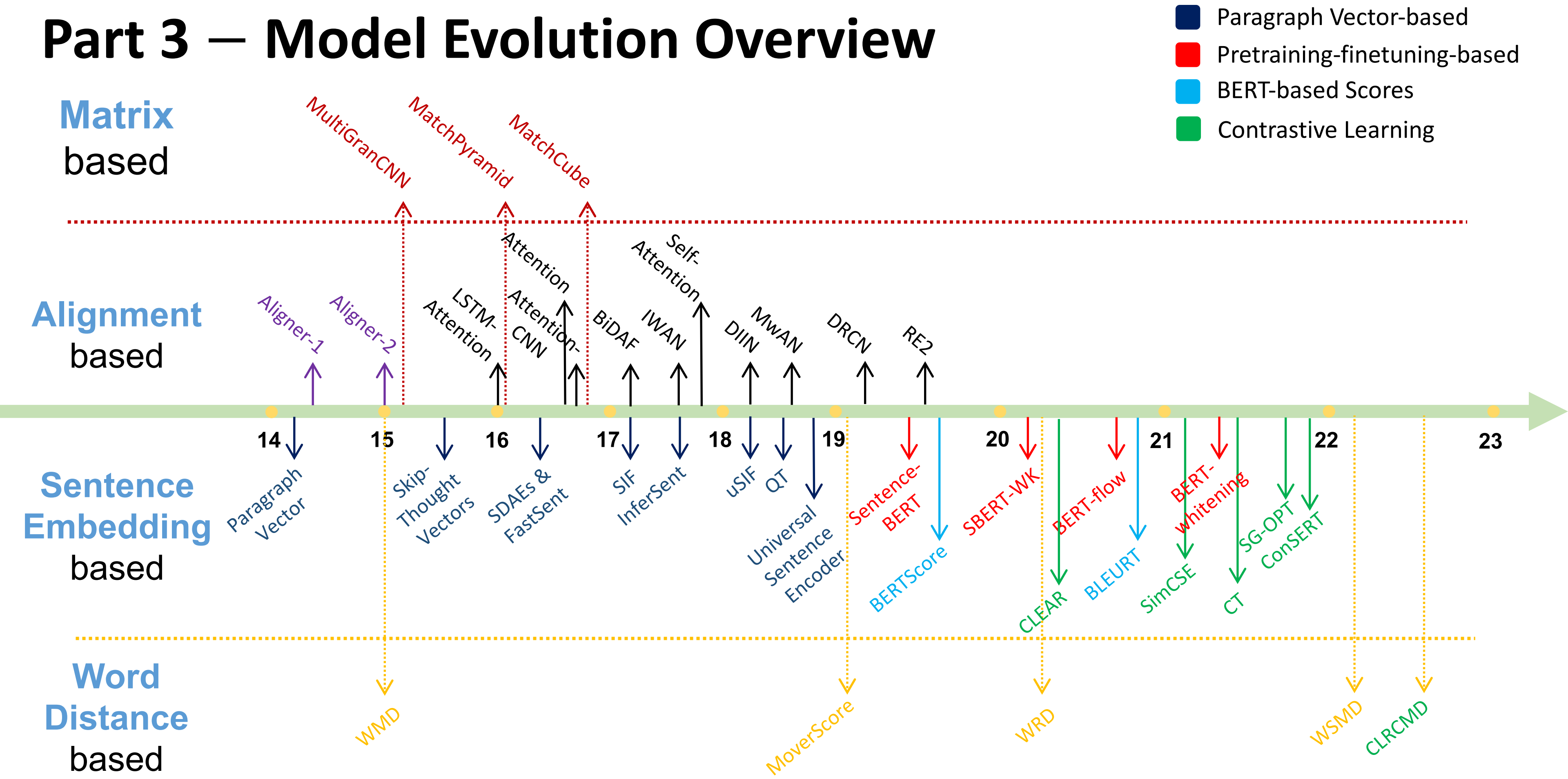
$$\mathrm{Jaccard}(w_1, w_2) = \frac{\sum_{w\in C(w_1)\cup C(w_2)} \min\big(P(w|w_1), P(w|w_2)\big)}{\sum_{w\in C(w_1)\cup C(w_2)} \max\big(P(w|w_1), P(w|w_2)\big)}.$$

- **Product Measure**

$$\mathrm{Product}(w_1, w_2) = \sum_{w\in C(w_1)\cup C(w_2)} \frac{P(w|w_1)\times P(w|w_2)}{\left(\frac{1}{2}P(w|w_1) + P(w|w_2)\right)^2}.$$

Credits:
Mohammad *et al.*, Distributional Measures of Semantic Distance: A Survey, In arXiv'12.

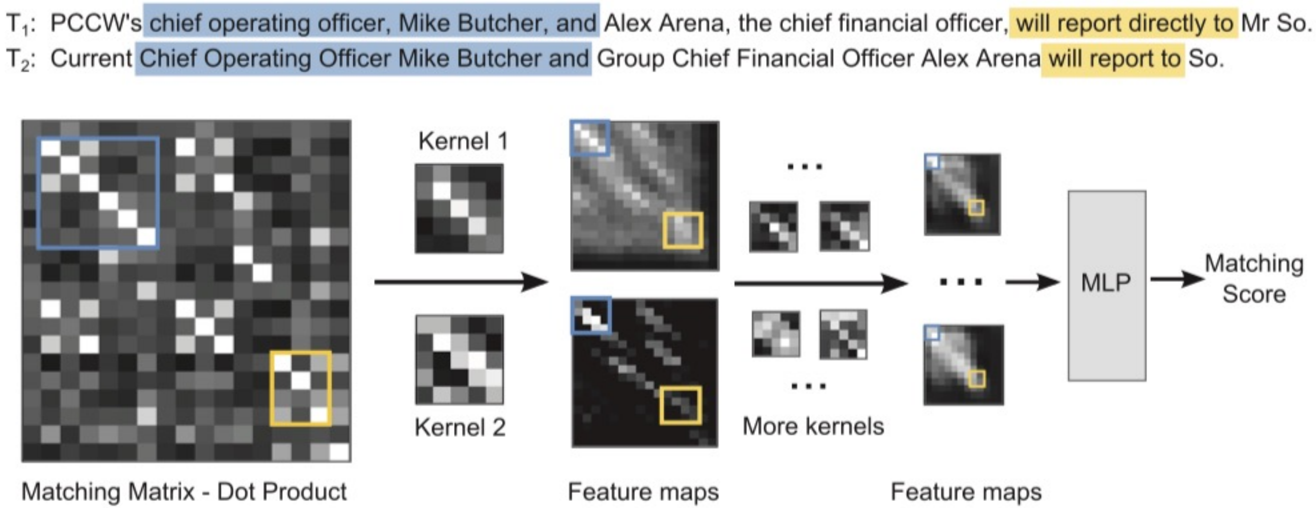
Part 3 — Model Evolution Overview



Part 4 — Matrix-based Methods

➢ **Key Idea**: construct a **similarity matrix** between two sentences, each element of which represents the similarity between the two corresponding units in two sentences. Then, the matrix is aggregated in different ways to induce the **final similarity score** [1]

Semantic Correspondence



Credits: [1] Sun *et al.*, Sentence Similarity Based on Contexts, In TACL'22. [2] Pang *et al.*, Text Matching as Image Recognition, In AAAI'16.

Part 4 — Matrix-based Methods

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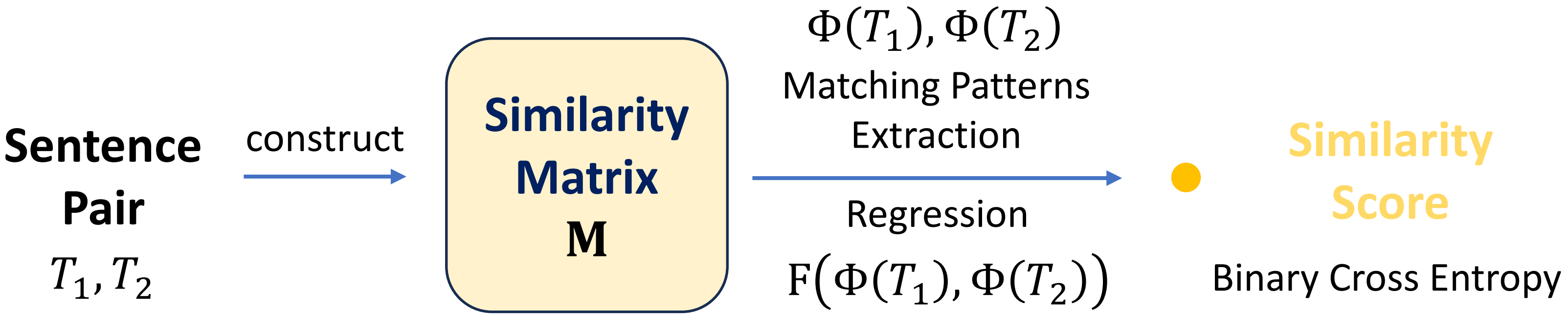

- **Similarity Matrix** (Matching Matrix) $\mathbf{M}$: similarity between word w_i and v_j, *e.g.*, cosine, dot product [2]
- **Feature Extraction and Regression**: $\Phi(\cdot)$: word embedding. $\mathrm{F}(\cdot)$: scoring function [2]

Credits: [1] Sun *et al.*, Sentence Similarity Based on Contexts, In TACL'22. [2] Pang *et al.*, Text Matching as Image Recognition, In AAAI'16.

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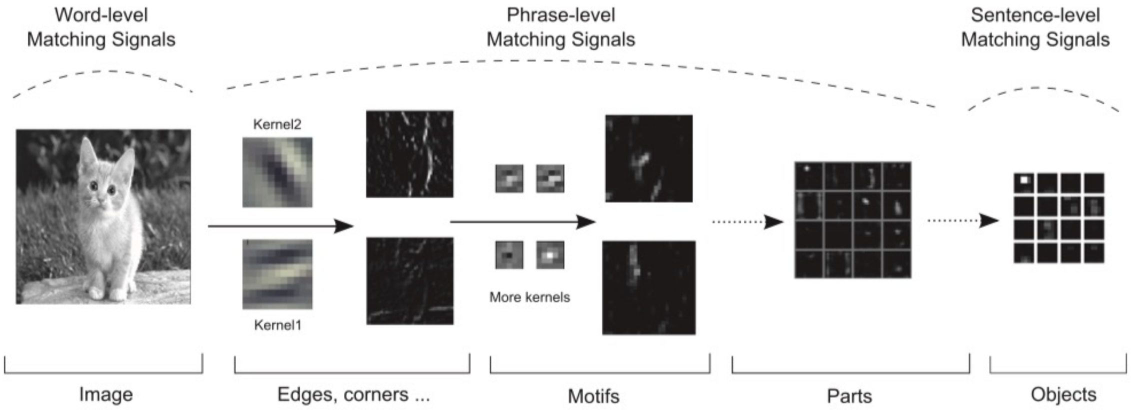


Figure 2: Relationships between text matching and image recognition.

Credits: [1] Sun *et al.*, Sentence Similarity Based on Contexts, In TACL'22. [2] Pang *et al.*, Text Matching as Image Recognition, In AAAI'16.

Part 4 — Matrix-based Methods

- **Similarity Matrix**:
  - Word2Vec → Cosine and dot product [1]
  - Bi-LSTMs → Pairwise interaction (Cosine, L_2, dot product) → Similarity focus via Weight [2]
  - MultiGranCNN → radial basis function kernel, inner product and sigmoid, weighted concat [3]

- **Feature Extraction and Regression**:
  - 2-layer CNN + 1-layer MLP [1]
  - 19-layer Deep ConvNet + 2-layer MLP [2]
  - mfCNN + 2-layer MLP [3]

Credits:
[1] Pang *et al.*, Text Matching as Image Recognition, In AAAI'16.
[2] He *et al.*, Pairwise Word Interaction Modeling with Deep Neural Networks for Semantic Similarity Measurement, In NAACL'16.
[3] Yin *et al.*, MultiGranCNN: An Architecture for General Matching of Text Chunks on Multiple Levels of Granularity, In ACL'15.

Part 5 — Alignment/Attention-based Methods

- **Key Idea**: Aligner aligns related words in two sentences

  Semantic similarity is a monotonically increasing function of the degree to which [1, 2]

  - The two sentences **contain similar semantic units**
  - Such units **occur in similar semantic contexts** in the respective sentences

- **Output**: Predict the pair's semantic similarity by **taking the proportion of their aligned content words**
- **Intuition**: More aligned semantic components ⇒ higher semantic similarity

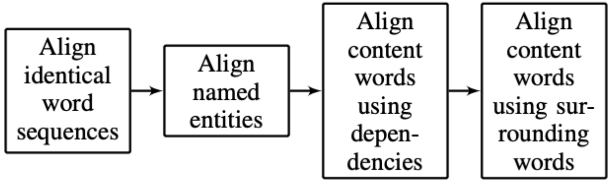


Figure 1: The alignment pipeline.

Credits:
[1] Sultan *et al.*, Back to Basics for Monolingual Alignment: Exploiting Word Similarity and Contextual Evidence, In TACL'14.
[2] Sultan *et al.*, DLS@CU: Sentence Similarity from Word Alignment, In SemEval'14.

Part 5 — Alignment/Attention-based Methods

- **Key Idea**: semantic alignment and comparison of two text sequences via Attention Mechanism
- **How**: Inter-sequence alignment layer

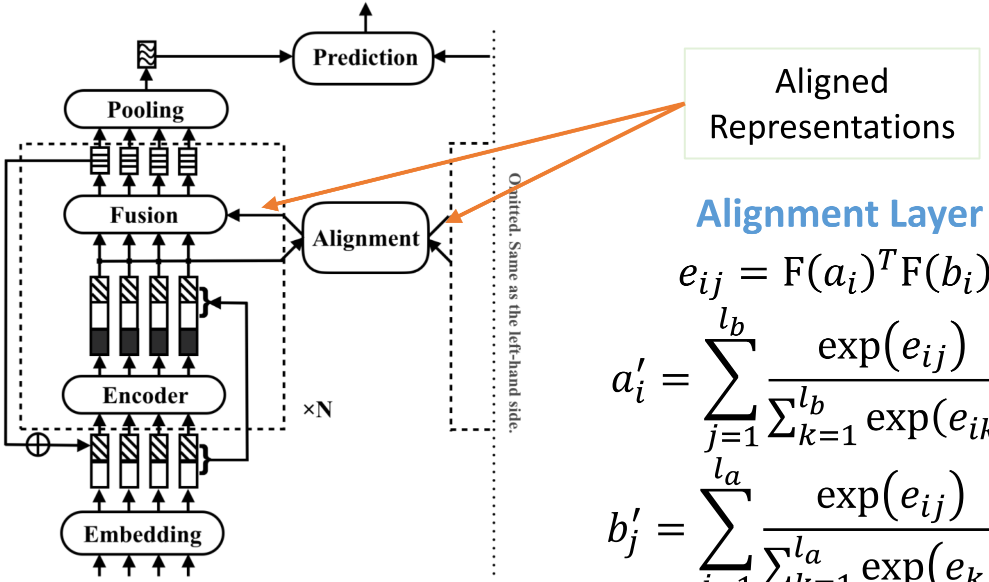
$$\hat{\mathrm{y}} = H([\mathrm{v}_1;\ \mathrm{v}_2; |\mathrm{v}_1 - \mathrm{v}_2|; \mathrm{v}_1 \circ \mathrm{v}_2]).$$

Fusion Layer

$$\bar{a}_i^1 = G_1([a_i; a_i']),$$
$$\bar{a}_i^2 = G_2([a_i; a_i - a_i']),$$
$$\bar{a}_i^3 = G_3([a_i; a_i \circ a_i']),$$
$$\bar{a}_i = G([\bar{a}_i^1;\ \bar{a}_i^2;\ \bar{a}_i^3]).$$

Augmented Residual Connections

$$x_i^{(n)} = \left[x_i^{(1)};\ o_i^{(n-1)} + o_i^{(n-2)}\right].$$



Alignment Layer

$$e_{ij} = \mathrm{F}(a_i)^T \mathrm{F}(b_i),$$

$$a_i' = \sum_{j=1}^{l_b} \frac{\exp(e_{ij})}{\sum_{k=1}^{l_b} \exp(e_{ik})} b_j,$$

$$b_j' = \sum_{i=1}^{l_a} \frac{\exp(e_{ij})}{\sum_{k=1}^{l_a} \exp(e_{kj})} a_i.$$

Credits: Yang *et al.*, Simple and Effective Text Matching with Richer Alignment Features, In ACL'19.

Part 6 – Word Distance-based Methods

- **Key Idea**: calculate the **cost of transferring** from one sentence to another
- **Intuition**: smaller cost $\Rightarrow$ more similar sentences
- **How**: **Earth Mover's Distance** (optimal transport cost) – the minimum cost required to turn one pile of dirt into another pile of dirt [1]
- **How**: **Word Mover's Distance** (WMD) – measure the dissimilarity between two documents as the **minimum amount of distance** that the embedded words of one document need to transform to words of another document [2]
- Each point x_i has a **probability mass** $m_i \in [0, 1]$. $c(\cdot)$ is a **transportation cost function**

$$\mu = \{(x_i, m_i)\}_{i=1}^{n}, \quad \mu' = \{(x'_j, m'_j)\}_{j=1}^{n'}.$$

$c(x_i, x'_j)$: determines the transportation cost per unit amount (distance) between two points x_i and x'_j.

Credits: [1] Villani *et al.*, Optimal Transport, In Springer'09. [2] Kusner *et al.*, From Word Embeddings to Document Distances. In ICML'15.

Part 6 — Word Distance-based Methods

- **Key Idea**: calculate the cost of transferring from one sentence to another
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$c(x_i, x'_j)$: determines the transportation cost per unit amount (distance) between two points x_i and x'_j $\Longrightarrow$ Alignment if c is small

$$\mathrm{EMD}(\mu, \mu'; c) := \min_{T \in \mathbb{R}_{\geq 0}^{n \times n'}} \sum_{i,j} T_{ij} c(x_i, x'_j),$$

$$\text{s.t.} \begin{cases} T\mathbb{1}_n = \mathrm{m} := (m_1, \ldots, m_n)^T, \\ T^T\mathbb{1}_{n'} = \mathrm{m}' := (m'_1, \ldots, m'_{n'})^T. \end{cases}$$

$\mathrm{EMD}(\mu, \mu'; c)$ is the cost of the best transportation plan between two distributions μ and μ'

$T \in \mathbb{R}_{\geq 0}^{n \times n'}$ denotes a transportation plan, where each element T_{ij} represents the mass transported from x_i to x'_j.

Credits: Yokoi *et al.*, Word Rotator's Distance, In EMNLP'20.

Part 6 — Word Distance-based Methods

- **Key Idea**: calculate the cost of transferring from one sentence to another
- **How**: Word Mover's Distance (WMD): is the cost of transporting a set of word vectors in an embedding space (Euclidean space)
- Each sentence s as a uniformly weighted distribution μ_s comprising word vectors w_i
- Transportation cost between word vectors $c_{\mathrm{E}}(w_i, w_j')$ is represented by Euclidean distance

$$\mu_s := \left\{\left(w_i, \frac{1}{n}\right)\right\}_{i=1}^{n},$$

$$\mu_s' := \left\{\left(w_j', \frac{1}{n'}\right)\right\}_{j=1}^{n'},$$

$$c_{\mathrm{E}}(w_i, w_j') := \|w_i - w_j'\|,$$

$$\mathrm{WMD}(s, s') = \mathrm{EMD}(\mu, \mu'; c_{\mathrm{E}}).$$

$\mathrm{WMD}(s, s')$ is defined as the EMD between two such distributions using the cost function $c_{\mathrm{E}}(w_i, w_j')$

Credits: Yokoi *et al.*, Word Rotator's Distance, In EMNLP'20.

Part 7 — Sentence Embedding-based Methods

Word → Sentence?

Linguistics = $\begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$

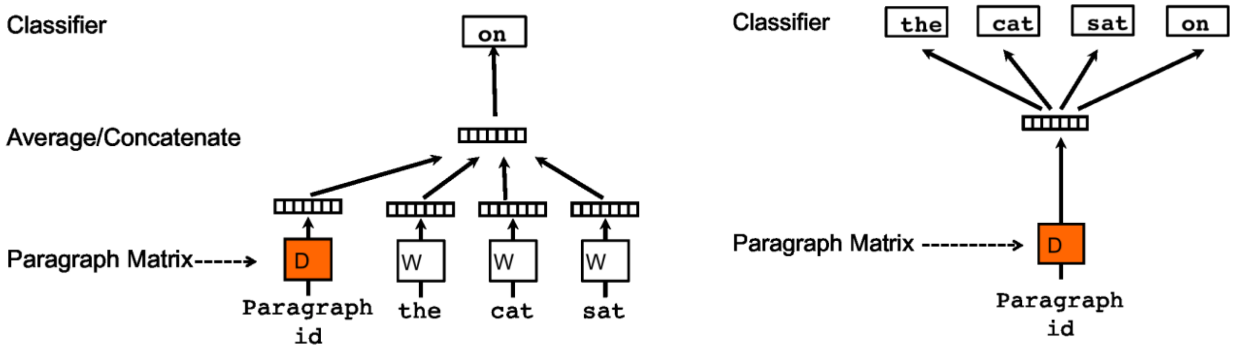
Natural language processing is fun. = $\begin{pmatrix} -0.132 \\ 1.129 \\ 0.827 \\ 0.110 \\ -0.527 \\ 0.156 \\ 0.349 \\ -0.286 \end{pmatrix}$

- Compute sentence similarity, *e.g.*, using the inner product
- Use as features for downstream tasks, *e.g.*, sentence classification

Credits: [CS224N Research Highlight (Presenter: Danqi Chen@Princeton)]

Part 7 – Sentence Embedding-based Methods

- **Key Idea**: **high-dimensional representations for sentences**. They are expected to contain rich sentence semantics so that the similarity between two sentences can be computed by **considering their sentence embeddings** via certain metrics such as cosine similarity
- **Paragraph Vector**: **fixed-length feature representations** from variable-length pieces of texts, such as sentences, paragraphs, and documents



Credits: Le *et al.*, Distributed Representations of Sentences and Documents, In ICML'14.

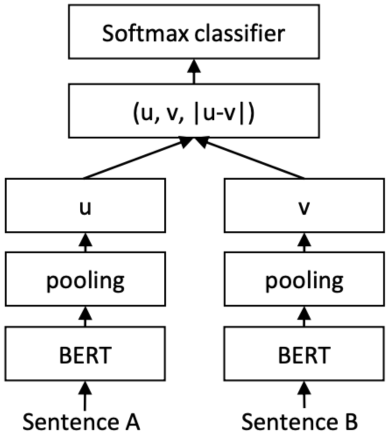
Part 7 — Sentence Embedding-based Methods

- **Paragraph Vector**: **fixed-length feature representations** from variable-length pieces of texts [1]
- Skip-Thought Vectors [2]
- Smooth Inverse Frequency (SIF) [3]
- Sequential Denoising Autoencoders (SDAEs) [4]
- InferSent [5]
- Quick-Thought Vectors [6]
- Universal Sentence Encoder [7]

Credits:
[1] Le *et al.*, Distributed Representations of Sentences and Documents, In ICML'14.
[2] Kiros *et al.*, Skip-Thought Vectors, In NeurIPS'15.
[3] Arora *et al.*, A Simple but Tough-to-beat Baseline for Sentence Embeddings, In ICLR'17.
[4] Hill *et al.*, Learning Distributed Representations of Sentences from Unlabelled Data, In NAACL'16.
[5] Conneau *et al.*, Supervised Learning of Universal Sentence Representations from Natural Language Inference Data, In EMNLP'17.
[6] Logeswaran *et al.*, An Efficient Framework for Learning Sentence Representations, In ICLR'18.
[7] Cer *et al.*, Universal Sentence Encoder, In arXiv'18.

Part 7 – Sentence Embedding-based Methods

- **Sentence Embedding**: **distributed representation of a sentence** in the form of a vector which encodes meaningful semantic information [Wikipedia]
- **Key Idea**: produce sentence embeddings based on the **pretraining-finetuning paradigm using large-scale unlabeled corpora**
- Sentence-BERT (SBERT) [1]
- SBERT-WK [2]
- BERT-flow [3]
- BERT-whitening [4]



Credits:
[1] Reimers *et al.*, Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks, In EMNLP’19.
[2] Wang *et al.*, SBERT-WK: A Sentence Embedding Method by Dissecting BERT-based Word Models, In IEEE/ACM T-ASLP’20.
[3] Li *et al.*, On the Sentence Embeddings from Pre-trained Language Models, In EMNLP’20.
[4] Su *et al.*, Whitening Sentence Representations for Better Semantics and Faster Retrieval, In arXiv’21.

Part 7 — Sentence Embedding-based Methods

- **BERT-based Scores Key Idea**: automatic evaluation metric for text generation

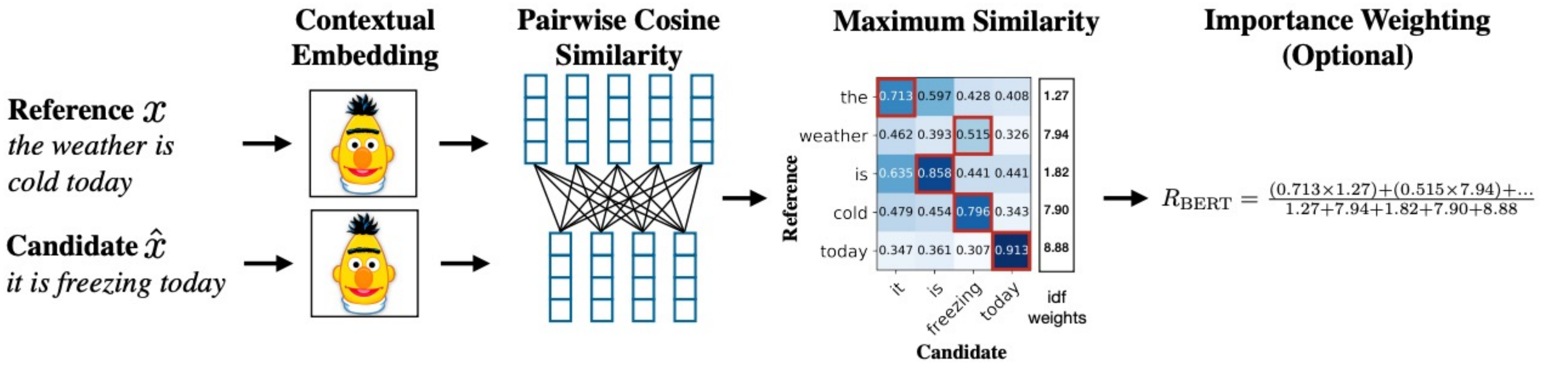


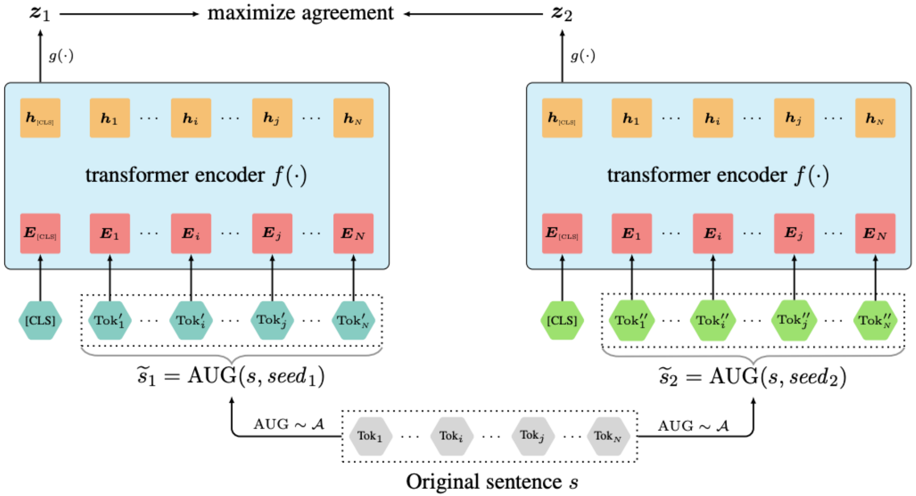
Figure 1: Illustration of the computation of the recall metric R_{BERT}. Given the reference x and candidate $\hat{x}$, we compute BERT embeddings and pairwise cosine similarity. We highlight the greedy matching in red, and include the optional idf importance weighting.

Credits:

[1] Zhang *et al.*, BERTScore: Evaluating Text Generation with BERT, In ICLR’20.
[2] Sellam *et al.*, BLEURT: Learning Robust Metrics for Text Generation, In ACL’20.

Part 7 — Sentence Embedding-based Methods

- **Contrastive Learning Key Idea**: two similar sentences are pulled close, and two random sentences are pulled away in the sentence representation space



Credits:

[1] Wu *et al.*, CLEAR: Contrastive Learning for Sentence Representation, In arXiv'20.
[2] Carlsson *et al.*, Semantic Re-tuning with Contrastive Tension, In ICLR'21.
[3] Kim *et al.*, Self-Guided Contrastive Learning for BERT Sentence Representations, In ACL'21.
[4] Yan *et al.*, ConSERT: A Contrastive Framework for Self-Supervised Sentence Representation Transfer, In ACL'21.
[5] Gao *et al.*, SimCSE: Simple Contrastive Learning of Sentence Embeddings, In EMNLP'21.

Part 8 — Evaluation Metrics for *Semantic Textual Similarity*

- **Pearson correlation** (Pearson Linear Correlation Coefficient) r — **measure the prediction accuracy**

$$r = \frac{\sum_{i=1}^{n}(s_i - \bar{s})\,(q_i - \bar{q})}{\sqrt{\sum_{i=1}^{n}(s_i - \bar{s})^2}\,\sqrt{\sum_{i=1}^{n}(q_i - \bar{q})^2}},$$

where s_i and q_i are the gold label and the model's prediction of the i-th sentence. $\bar{s}$ and $\bar{q}$ are the mean values of $\mathbf{s}$ and $\mathbf{q}$. n is the number of sentences.

- **Spearman's rank correlation** (Spearman's Rank-order Correlation Coefficient) ρ — **measure the prediction monotonicity**

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)},$$

where d_i is the difference between the i-th sentence's rank in the model's predictions and gold labels.

Part 9 — Benchmark Databases

0: Dissimilar

Synonymous

Dataset Name	Word/Sentence pairs	Similarity score range	Year	Reference
R&G	65	0–4	1965	[107]
M&C	30	0–4	1991	[78]
WS353 Relatedness	353	0–10	2002	[30]
LiSent	65 Sentences	0–4	2007	[63]
SRS Biomedical	30	0–4	2007	[94]
WS353-Sim	203	0–10	2009	[1]
STS2012	5,250 Sentences	0–5	2012	[5]
STS2013	2,250 Sentences	0–5	2013	[6]
WP300	300	0–1	2013	[61]
STS2014	3,750 Sentences	0–5	2014	[3]
SL7576	7,576	1–5	2014	[116]
SimLex-999	999	0–10	2014	[40] 900 Similar Word Paris
SICK-Relatedness	10,000 Sentences	1–5	2014	[69]
STS2015	3,000 Sentences	0–5	2015	[2]
SimVerb	3,500	0–10	2016	[34]
STS2016	1,186 Sentences	0–5	2016	[4]
WiC	5,428	NA	2019	[97]
STS Benchmark	8628	0-5	2017	[Link]

Credits: Chandrasekaran *et al.*, Evolution of Semantic Similarity—A Survey, In ACM Computing Survey'21.

Part 10 – Takeaways

- **Distance Measurement**
- **Spatial Metrics**
  - Cosine Similarity
  - Manhattan Distance or L_1 Norm
  - Euclidean Distance or L_2 Norm
- **Mutual Information**
  - Hindle
  - Lin
- **Relative Entropy**
  - Kullback-Leibler Divergence (KLD) – Common Occurrence, Absolute, Average, and Maximum
  - $\boldsymbol{\alpha}$-skew Divergence (ASD)
  - Jensen-Shannon Divergence (JSD)
- **Others**
  - Co-occurrence Retrieval Models (CRM), Dice Coefficient, Division Measure, Jaccard, Product Measure

Credits: Mohammad *et al.*, Distributional Measures of Semantic Distance: A Survey, In arXiv'12.

Part 10 – Takeaways

Evolution of Semantic Similarity

- **Knowledge-based Methods**

  Pros: consider the actual meaning of the text

  Cons: not adaptable across different domains and languages

- **Corpus-based Methods**

  Pros: have a statistical background and can be implemented across languages

  Cons: don’t consider the actual meaning of the text

- **Deep Learning-based Methods**

  Pros: better performance

  Cons: require high computational resources and lack interpretability

- **Hybrid Methods**

  Pros: take advantage of the benefits of different methods

Credits: Chandrasekaran *et al.*, Evolution of Semantic Similarity—A Survey, In ACM Computing Survey’21.

Part 10 – Takeaways (This one is generated by ChatGPT)

➢ **Deep Learning-based Methods** (Note: Some works may combine the following ideas.)

- **Matrix-based Methods**

  Pros: scalability for handling large datasets efficiently and Interpretability for clear alignment between words

  Cons: sensitivity to length (larger matrices and potentially skewed similarity scores) and sparse matrices that make it challenging to capture nuanced relationships between words.

- **Alignment-based Methods**

  Pros: better identify word-level and fine-grained correspondences between sentences

  Cons: computationally intensive and not robust to paraphrasing

- **Word Distance-based Methods**

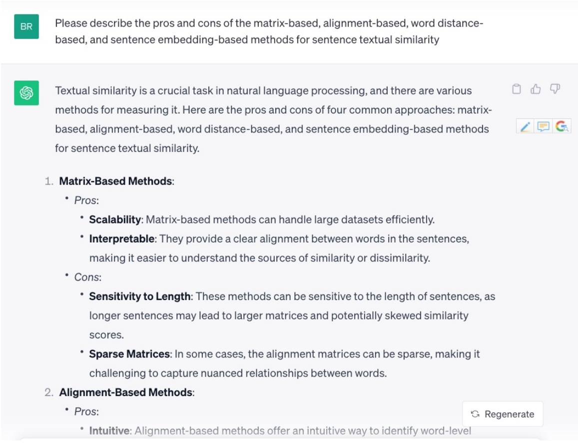
  Pros: straightforward to implement and sensitive to Word Choice

  Cons: order insensitivity and lack of context

- **Sentence Embedding-based Methods**

  Pros: robust to syntax and versatile

  Cons: loss of fine-grained Information and embedding quality



Part 10 — Takeaways

- **Evaluation Metrics**:
  - **Pearson correlation** r — **measure the prediction accuracy**

$$r = \frac{\sum_{i=1}^{n}(s_i - \bar{s})(q_i - \bar{q})}{\sqrt{\sum_{i=1}^{n}(s_i - \bar{s})^2}\sqrt{\sum_{i=1}^{n}(q_i - \bar{q})^2}}.$$

  - **Spearman's rank correlation** ρ — **measure the prediction monotonicity**

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}.$$

- **Benchmark Databases**:
  - STS12, STS13, STS14, STS15, STS16, STS Benchmark (STSb), and SICK-Relatedness
- **Note**: Other related tasks have their own set of benchmarks and specific evaluation metrics.

Thank you very much for your attention!

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