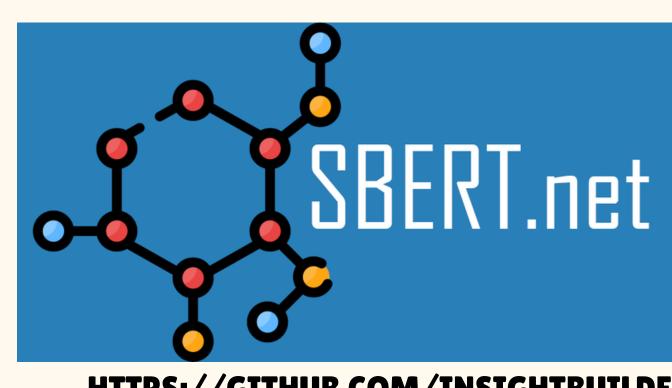
# EXPLORING THE POWER OF

EMBEDDINGS WITH CLUSTERING INSIGHTS SAVING **GROOTENDORST, MAARTEN BERTopic** COST + LIFE EMBEDDING

RAW DATA

BUILDING BRIDGES BETWEEN DATA & INSIGHTS IN THE AI ERA



DECISION

HTTPS://GITHUB.COM/INSIGHTBUILDER

### CHALLENGE SOLVED: WHERE & HOW EMBEDDINGS ARE USED

- REAL LIFE APPLICATION:
  - MARKET SEGMENTATION
  - IMAGE SEGMENTATION (CANCER CELL DETECTION)
  - ANAMOLY DETECTION (CREDIT CARD / NETWORK ANALYSIS)
  - LAND / NETWORK USAGE ANALYSIS
  - **O SEARCH ENGINES**
  - CROSS ENCODERS
  - **O IMAGE SEARCH**
- ANY APPLICATION THAT WILL REQUIRE
   CLUSTERING IN VOICE, VIDEO ALSO CAN WORK

- CLUSTERING ALGORITHMS / PROCESSES:
  - PARTITION CLUSTERING
    - K-MEANS
  - DENSITY BASED CLUSTERING
    - MEAN-SHIFT ALGORITHM
  - DISTRIBUTION MODEL-BASED CLUSTERING
    - DENSITY BASED SPATIAL CLUSTERING & NOISE
  - HIERARCHICAL CLUSTERING
    - AGGLOMERATIVE CLUSTERING
    - AFFINITY PROPOGATION
  - FUZZY CLUSTERING

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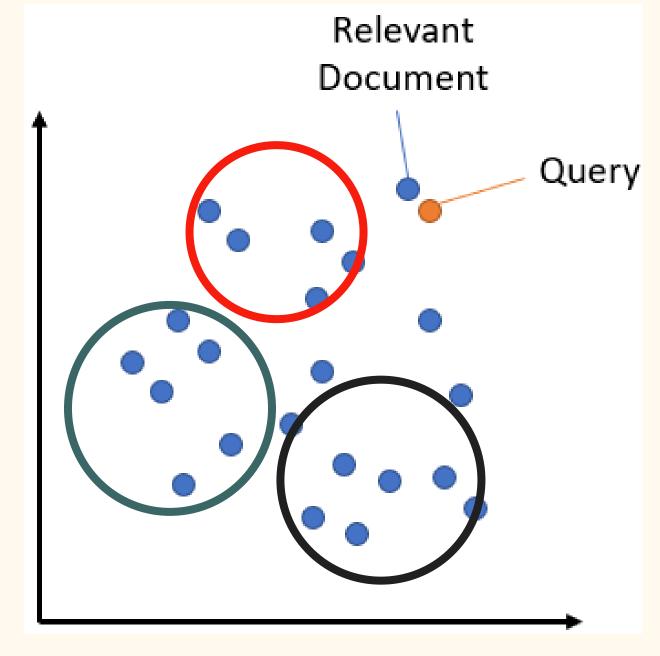
## **OPEN SOURCE LIBARIES: CHALLENGES THEY SOLVE**

- SENTENCE-TRANSFORMERS: PROVIDE EMBEDDING (HTTPS://WWW.SBERT.NET)
- BERTOPIC: TOPIC MODELING + VISUALISATION (HTTPS://MAARTENGR.GITHUB.IO/BERTOPIC)
- PICKLE: SAVE THE EMBEDDING DATA AS FILE
- SAFETENSOR: SAFER ALTERNATIVE OF SAVING EMBEDDING DATA
- KEYBERT: EXTRACTING KEYWORDS FROM CORPUS
- SKLEARN: PROVIDE ML ALGORITHMS FOR CLUSTERING
- HDBSCAN: LIBRARY FOR DOING DBSCAN CLUSTERING + LOT MORE (HTTPS://HDBSCAN.READTHEDOCS.IO/)
- TRANSFORMERS: LOAD NEURAL NETWORK MODELS, TRAIN & PREDICT OUTPUT
- PYTORCH: CREATE NEURAL NETWORK MODEL AND TRAIN + PREDICT OUTPUT
- HUGGINGFACE\_HUB: SAVE AND LOAD NEURAL NETWORK MODELS IN THE HUB
- RAPIDS: MOVE THE ML OPERATIONS TO GPU (RAPIDS.AI)

#### HTTPS://GITHUB.COM/INSIGHTBUILDER

### **CLUSTERING: DOES NATURE CREATE CLUSTERS**

- NATURE JUST CREATES, MATH ALGORITHMS PLACE
  THE CIRCLES OVER THE CREATIONS TO MAKE LIFE OF
  THE OBSERVER EASIER
- WHAT TO DO WITH THE OUTLIERS? WHY DO THE EXIST
- MODEL THAT CAN CHOOSE WHICH BAG THE DATA
   POINT WILL GO IS EASY TO CREATE.
- WHEN THE NUMBER OF POINTS INCREASES THEN THE QUESTION OF WHETHER TO INCREASE THE BAGS ARISES
- CAN THERE BE CLUSTERS WITHIN CLUSTERS? HIERARCHY.
- WHAT IF I DON'T KNOW ANYTHING ABOUT NUMBER OF CLUSTERS AVAILABLE



AND WHAT ABOUT THE
TOPICS OF THESE
CLUSTERS?

OPIC MODELS:
TYPES &
METHODS
PROXIMATE TOPIC DISTRIBUTION

WITH SLIDING WINDOW ON DOCS ONLINE TOPIC MODELING IS USED

WHEN DATA IS FLOWING

- INCREMENTALLY SEMI-SUPERVISED CAN HELP IF YOU
- HAVE SOME CATEGORIES AVAILABLE. • SUPERVISED MODELING INVOLVES
- **REGRESSION TO TRAIN**
- MANUAL MODE SKIPS DIM REDUCTION & CLUSTERING. HEADS TO TOPIC
- GUIDING THE TOPICS WITH SIMILARITY
- USING C-TF-IDF TO CREATE

**SEARCH** 

HIERARCHICAL CLUSTERING LOOKING AT THE TOPIC CHANGING

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Online Topic Modeling

**Manual Topic Modeling** 

**Dynamic Topic Modeling** 

Method

**Topic Distribution Approximation** 

.approximate\_distribution(docs)

.partial\_fit(doc)

Code

.fit(docs, y=y)

.fit(docs, y=y)

Semi-supervised Topic Modeling

.fit(docs, y=y)

**Multimodal Topic Modeling** 

.fit(docs, images=images)

**Topic Modeling per Class** 

.topics\_over\_time(docs, timestamps)

.hierarchical\_topics(docs)

.topics\_per\_class(docs, classes)

**Hierarchical Topic Modeling** 

**Guided Topic Modeling** BERTopic(seed\_topic\_list=seed\_topic\_list)

WITH DYNAMIC TOPIC MODELING

**Supervised Topic Modeling** 

# THANKS FOR WATCHING REMEMBER TO PRACTICE WITH EXAMPLES

LIKE SHARE SUBSCRIBE