# Generative AI and Symbolic Knowledge Representations LLMs, Knowledge and Reasoning 3

Damir Cavar & Billy Dickson ESSLLI 2024

July 2024

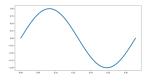
#### Continuation

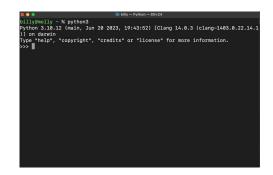
- LLMs and NLP
- Code examples:
  - Vectorization and embeddings

#### **LLMs and Tools**



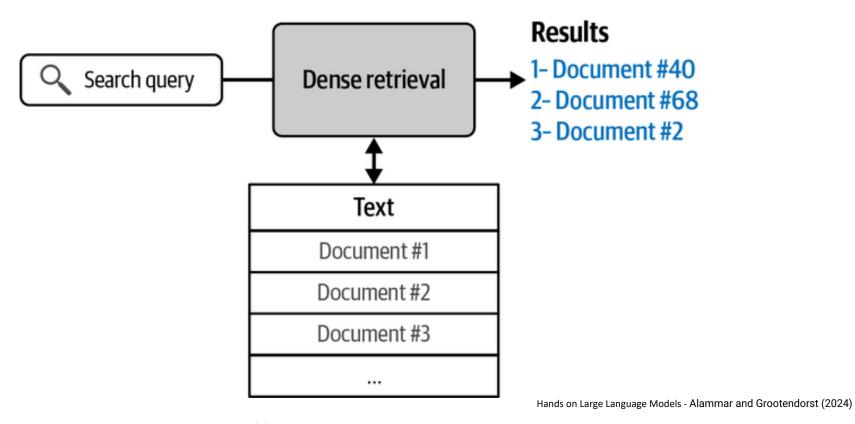




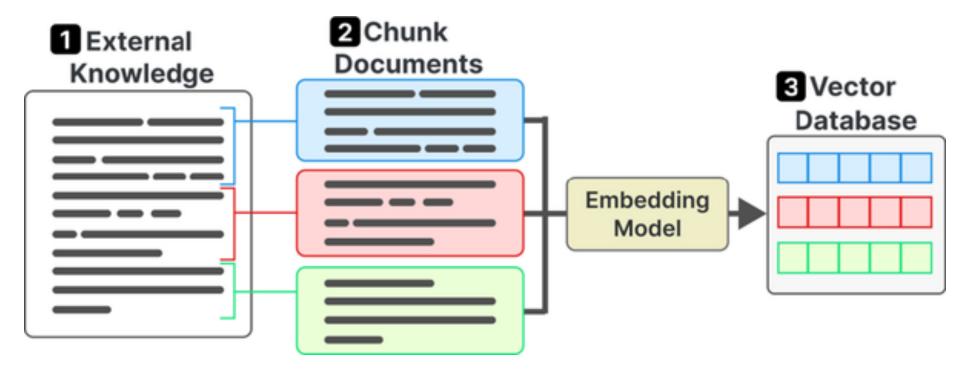




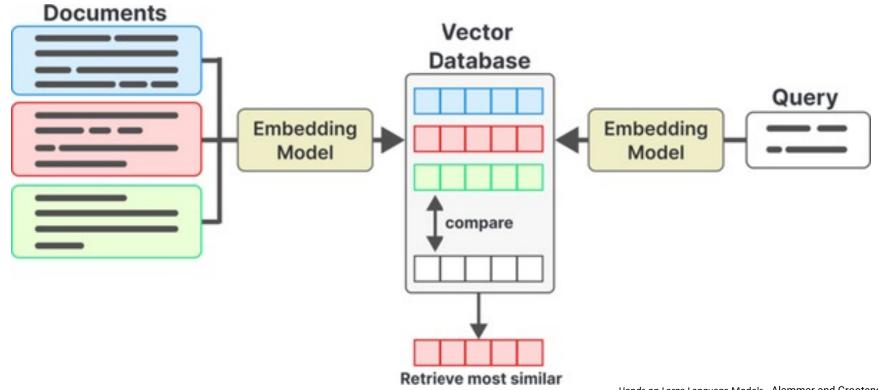
#### **Dense Retrieval**



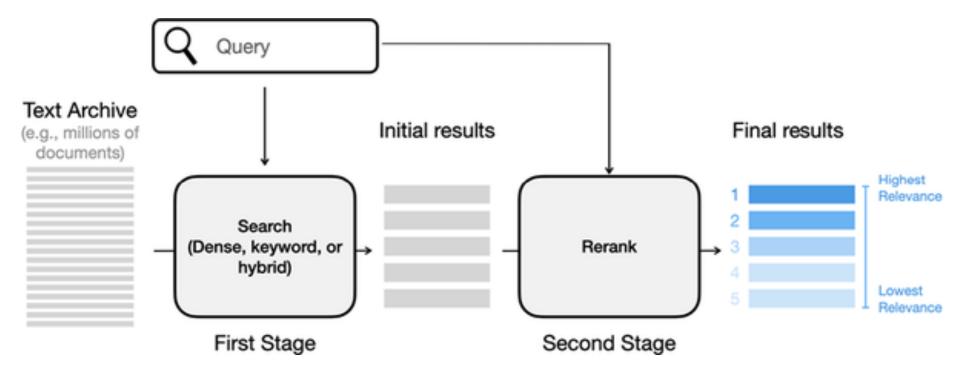
(C) Cavar & Dickson - ESSLLI 2024 Course



Hands on Large Language Models - Alammar and Grootendorst (2024)

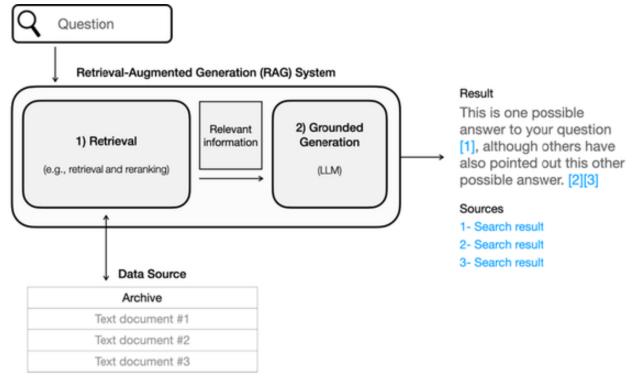


# Reranking

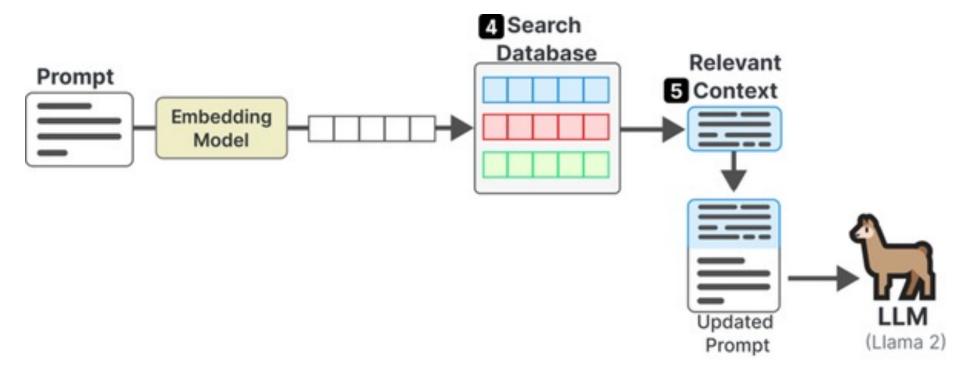


Hands on Large Language Models - Alammar and Grootendorst (2024)

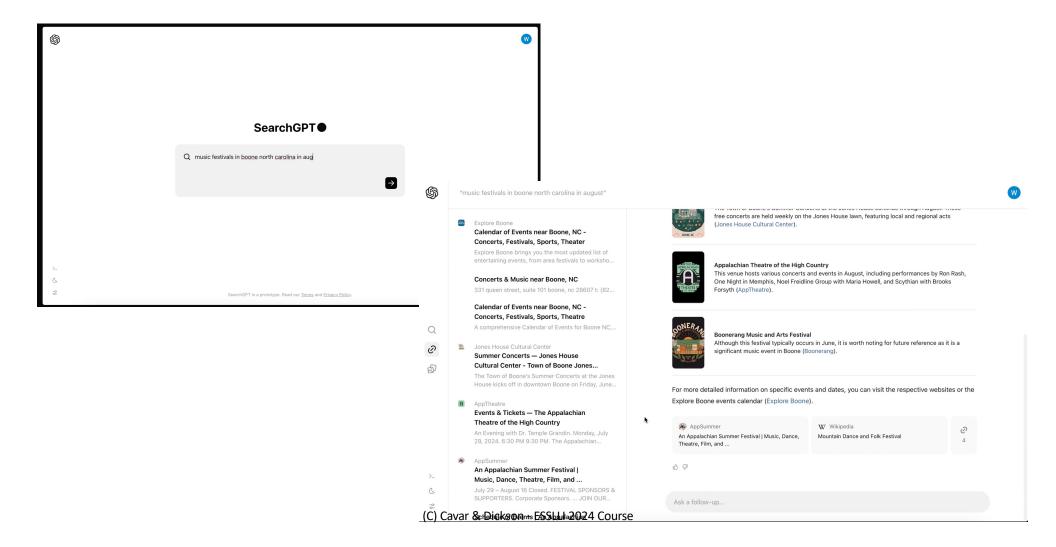
(C) Cavar & Dickson - ESSLLI 2024 Course



Hands on Large Language Models - Alammar and Grootendorst (2024)



Hands on Large Language Models - Alammar and Grootendorst (2024)



## Knowledge

- Passive knowledge
  - Canned text
    - Question/Query + Response/Answer
    - Response:
      - Text
      - Code
      - Image
  - Indexing response for a given query?
    - Query: vector
    - Response index: vector
    - Match: vector similarity, approximate distance in semantic space, find K Nearest Neighbors...

# Symbolic Knowledge Representations

- Knowledge Graphs
- Ontologies
- Reasoning

#### Goals

- Build the models, infrastructure, technologies to
  - engineer AI systems with advanced computational semantics and pragmatics capabilities
    - Description Logic
    - Temporal Logic
    - Event Semantics
  - Build data sets with semantic annotations (multi-modal: text, speech, image) for training and evaluation of ML models
- Application domains:
  - Discourse Models
  - Text forensics:
    - Fake news, propaganda, and deception detection
  - Domain specific:
    - Medical, Business, ...

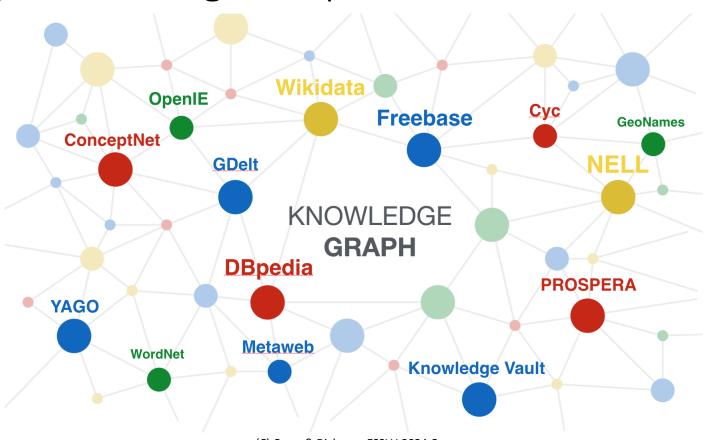
# Knowledge and Computing

- Model World Knowledge Linguistically Motivated Computational Processing
  - Meaning of words
  - Meaning of speech acts (including Presuppositions, Implicatures, Events, Temporal Logic)
  - Computational Models of World Knowledge / Common Sense in phenomena like Binding, Anaphora Resolution, Reasoning
    - "Take the knife, cut the lime in half, and put it down." it = knife
    - "Take the knife, cut the lime in half, and squeeze it." it = lime

### Objectives

- Multi-Modality
  - Language, Speech, Vision, Sensory Information, ...
- Deep Semantic and Pragmatic Processing
  - High precision
  - Deep insights
- High Performance Computation for Big Data Analysis
  - Scalability (Speed, Memory)
  - Efficient Parallel Algorithms

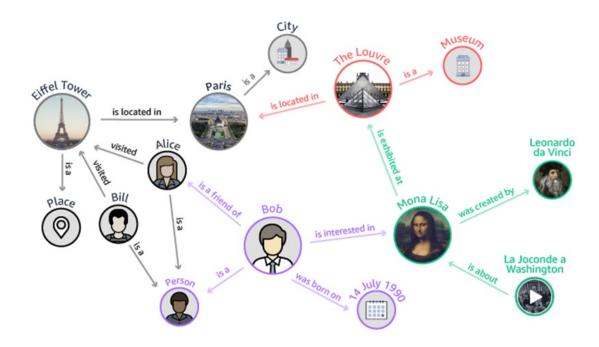
# Large Knowledge Graphs



10/2/2/4/24

(C) Cavar & Dickson - ESSLLI 2024 Course

# Knowledge Graphs



## Knowledge Representations

- Model (or Ontology) and Individuals (or Assertions of Facts)
- Model: Web Ontology Language (OWL) as a restrictive model/ontology specifying
  - Concepts (or entity types)
  - Relations (between entities, instances of concepts or entity types)
  - Properties of Concepts and Relations
- Individuals
  - Concrete instances of concepts and relations

# Knowledge Graphs

Concepts and Relations

• Mostly unconstrained

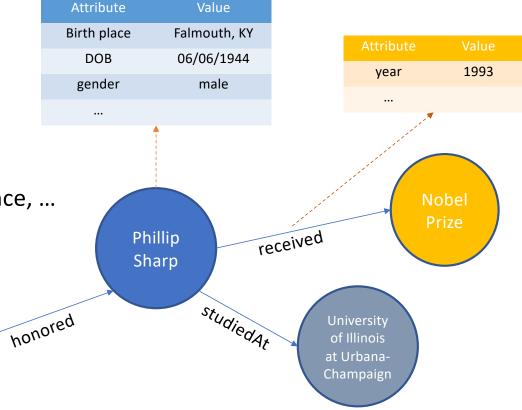
• Domain specific or free

Attributes and Values

• encoding properties, time reference, ...

George

W. Bush



#### **Focus**

- Knowledge Representations
  - Description Logic
    - Probabilistic
    - Dynamic
  - Events
    - Temporal Logic
      - Event sequences and durations
    - Resource Logic
      - Transfer of resources
      - Intentionality

# **Knowledge Graphs**

- Formally:
  - Sets of triples:
    - Subject Predicate → Object
  - Quad notation:
    - Sets of triples grouped by a 4<sup>th</sup> element
      - Graph ID
      - Temporal ID
      - Event ID
      - **–** ...

# Knowledge Representations

Confidence Scores

Qualitative metric for source

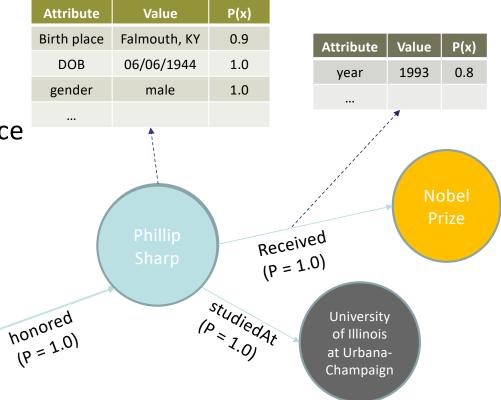
- Quantitative metric for evidence

Scoring

Sources wrt. Reliability

Counts of entity property or

relation



## **Knowledge Graphs**

- No computation or interpretation of logic equations (e.g., no access to universal or existential quantifiers)
- Direct mapping of knowledge from language input limited to Description Logic
- Description of Knowledge
  - Directed Graph: encoding concept, events, domain specific knowledge...
  - Attribute-Value encoded features like size and shape, but also event time references (start, end, duration), etc.
- Reasoning: OWL & Reasoner, Common Graph Algs.
- Prediction: Links, Class prediction, etc.
- Machine Learning of concepts and concept properties: node or edge embedding

### Reasoning

- Validation of assertions
- Entailment computation
- Link prediction
- Entity classification
- Question Answering and Dialog
- Domains:
  - Medical, FinTech, Legal, Cybersecurity, ...

#### Resources

- General Knowledge Knowledge Graphs
  - DBpedia
  - YAGO
  - ConceptGraph
  - **—** ...
- Domain Specific Knowledge Graphs
  - Unified Medical Language System (UMLS)
  - USDA Food Database
  - CyGraph

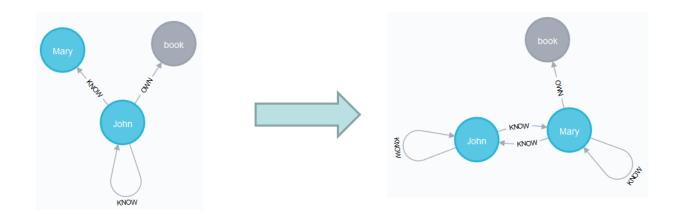
**–** ...

# **Knowledge Graphs**

- Static: Concept and Relation Properties
  - Even when dynamically growing or changing
- Problem to encode events or procedures
  - Mary gave John a book.
    - Event as a state change / transformation:
      - Mary owns a book, John does not → John owns a book, Mary does not
  - Peter was fetching his daughter from school.
    - Intermediate states:
      - Peter is at home, daughter at school → Peter is at school, daughter at school →
        Peter is at home, daughter at home

#### **Events and Resources**

John gave Mary a book.



- Events as sequences of graphs and graph transformations
  - Encoding of Intentionality

### Temporal Relations

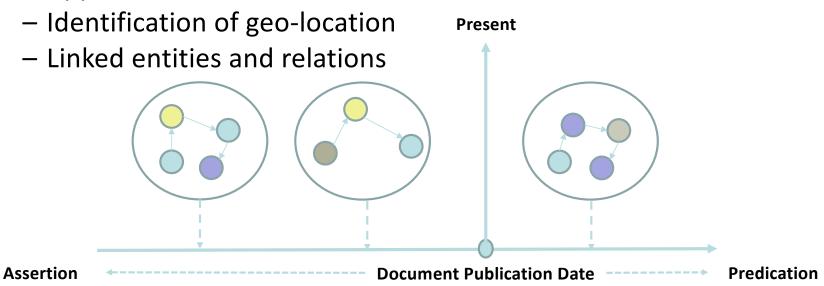
- Sequencing of events or sub-events
  - Wash the veggies, chop them, fry them.
    - Presentation and Temporal event sequence: 1 2 3
  - Before you fry the veggies, wash and chop them.
    - Presentation sequence: 3 1 2
    - Temporal event sequence: 1 2 3
- Duration of events
  - Clear reference: "for 30 minutes"
  - Common sense

# Temporal Relations

- Duration of events
- Unfolding over time
  - Events relate to time
  - States are points in time
- Temporal sequencing relates to
  - Causal reasoning

### **Event Graphs**

- Arrangement of sub-events along time axis
  - Approximation of duration



# **Graphlets of Events and States**

#### Graphlets

- Sub-graphs using a point in time
- Temporal sequencing of events in time = graphlets

#### Technically

- Graphs and Graphlets use temporal timestamps as properties
  - Temporal reference
  - Event ID or variable

## Temporal Scope

- Simple temporal relations
  - Past tense: Tim Cook bought Google.
    - Assumptions: factive, true event
  - Future tense: Tim Cook will buy Google.
    - Assumptions: non-factive, hypothetical
- Complex relations: temporal scope
  - Reuters reported that

Tim Cook bought Google

• Reuters will report that

### Temporal Scope

- Sub-event triples:
  - Tim Cook buy → Google
  - Event-ID is  $\rightarrow$  43829
- Dominating event triples:
  - Reuters report → eventX
  - eventX hasID→ 43829
  - eventTime ...
  - speakerTime ...
  - referenceTime ...

#### **NLP Extensions**

- Implicatures:
  - John to Peter: I bought the blue car.
    - John and Peter talked about cars earlier.
    - · There should be a set with at least one more car the John could have bought, but did not, and
    - None of the cars in the set is blue.
  - Clues: Definiteness of NP via the, and specificity of NP
- Presuppositions:
  - John fed his cat this morning.
  - Assumptions:
    - John owns/has a cat/pet.
    - John owned cat-food this morning.
  - Clues: Possessive pronoun as modifier of Direct Object.

### Pragmatics and Implicatures

- Input: Mary is the sister of Tracy.
  - → Mary -> gender: female
  - → Mary hasSibling Tracy, Tracy hasSibling Mary

• • •

- Input: Donald Trump met Vladimir Putin.
  - → Vladimir Putin met Donald Trump
- Input: I regret that I drank a coffee.
  - → Claimed to be a fact / true: I drank coffee.
- Input: Tom parked his car in the Atwater garage.
  - → Tom knows how to operate a car.
  - → Tom was in possession of a car.

•••

- And many more...
- Knowledge of language (universal and particular) is necessary to generate these presuppositions and implicatures.

# Pragmatics and World Knowledge

- Scenario in Medical
  - Medication Metformin found in pocket of unconscious person:
    - → Patient might have (Type-2) diabetes.
- Domain specific knowledge (Knowledge Graph) is necessary to resolve the drug name and reason about the diagnosis.

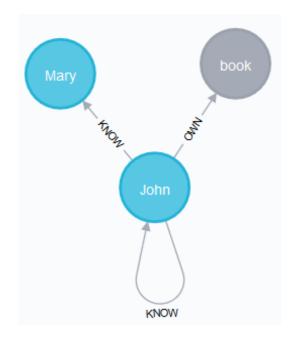
- Veridicality
  - Factive predicates: *know*, *regret*, *realize*, *notice*, ...
    - *I regret that* ... (X did something to Y)
    - Complements are assumed to be true
  - Non-factive predicates: believe, think, claim, ...
    - I believe that ... (X did something to Y)
    - Complements cannot be assumed to be true
  - Counter-factive predicates: pretend, ...
    - John pretends that he is ill.
    - Complement cannot be true: John is not ill
- Question:
  - Cross-linguistic similarity = universal properties related to factivity

- Predicative Properties
  - Functional
    - $X \rightarrow hasBirthMother \rightarrow Sue \& X \rightarrow hasBirthMother \rightarrow Susan$
    - Implies: Sue & Susan are identical entities
  - Inverse functional
    - Same as Functional, just for the inverse predicate: isBirthMotherOf
  - Transitive
    - X → hasAncestor → Y → hasAncestor Z
    - Implies: X → hasAncestor → Z
  - Symmetry
    - $X \rightarrow met \rightarrow Y$
    - Implies:  $Y \rightarrow met \rightarrow X$
  - Asymmetry
    - $X \rightarrow isChildOf \rightarrow Y$
  - Reflexive
    - $X \rightarrow knows \rightarrow Y$
    - Implies:  $X \rightarrow knows \rightarrow X$
  - Irreflexive
    - Any relation where X → relation → Y implies X cannot be Y

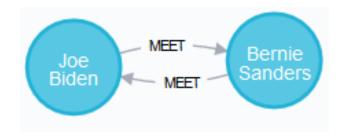
- Functional
  - X → hasBirthMother → Sue & X → hasBirthMother → Susan
  - Implies: Sue & Susan are identical entities
- Inverse functional
  - Same as Functional, just for the inverse predicate: isBirthMotherOf
- Transitive
  - X → hasAncestor → Y → hasAncestorZ
  - Implies: X → hasAncestor → Z
- Symmetry
  - $-X \rightarrow met \rightarrow Y$
  - Implies: Y  $\rightarrow$  met  $\rightarrow$  X

- Asymmetry
  - $-X \rightarrow isChildOf \rightarrow Y$
- Reflexive
  - $X \rightarrow knows \rightarrow Y$
  - Implies: X → knows → X
- Irreflexive
  - Any relation where X → relation → Y implies X cannot be Y
- Strong cross-linguistic similarity
  - Universal?

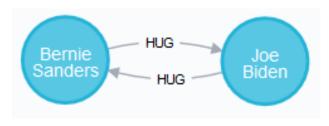
- Reflexive
  - $-X \rightarrow knows \rightarrow Y$
  - Implies: X → knows → X



- Symmetry or Reciprocity
  - $-X \rightarrow met \rightarrow Y$
  - Implies: Y  $\rightarrow$  met  $\rightarrow$  X



- Also:
  - Bernie and Joe hugged each other.



- Veridicality
  - Factive predicates: know, regret, realize, notice, ...
    - I regret that ... (X did something to Y)
    - Complements are assumed to be true
  - Non-factive predicates: believe, think, claim, ...
    - I believe that ... (X did something to Y)
    - Complements cannot be assumed to be true
  - Counter-factive predicates: pretend, ...
    - John pretends that he is ill.
    - Complement cannot be true: John is not ill
- Question:
  - Cross-linguistic similarity = universal properties related to factivity

### Typing and Predicates

- Verb Frames and Predicate Properties
  - Type information for arguments
  - Differentiation between
    - Modifiers: for properties of entities and relations in DL graphs
    - Arguments: core entities and relation links in DL graphs

## Semantic Mapping and Reasoning

- Type of Predicative Arguments: Typing
  - Named Entity Recognition
  - Closes possible Hypernym in a Taxonomy or Ontology of isA relations
- Identity of entity: Linking
  - Named Entity Recognition
  - Link to unique identifier of entity in some knowledge representation,
    Ontology, Wikipedia, Knowledge Graph
- Issues: Ambiguity

## Graph Extraction and Linking

- Graph generation sample:
  - NLP pipelines
  - Graph extraction
  - Linking (conceptualization, language independent representation)
- Goal:
  - Extract predicate-argument tuples
  - Type the entities (e.g. NER, ontology lookup, Knowledge Graph linking)
  - Dynamically expand the knowledge graph and track weights (probabilities)

### Linking Strategy

- 1 to *n* relation between entity and entities in Knowledge Graphs
- Disambiguation via Geometrical Similarity
  - Text representation as average vector of word embeddings (e.g. Numberbatch, Glove, Bert)
  - Graph as average vector of concept and edge embeddings
- Maximization of context word prediction for each linking candidate
- KGs:
  - YAGO, ConceptNet, MS Word Graph, etc.

### Linguistic Bias

- Pragmatic effects in language use data (e.g. Sperber & Wilson's Relevance Theory, Grice's Maxims)
  - People communicate facts and information that is relevant, new, exciting
  - Observation:
    - Exciting information: purple carrots



Less exciting information: orange carrots

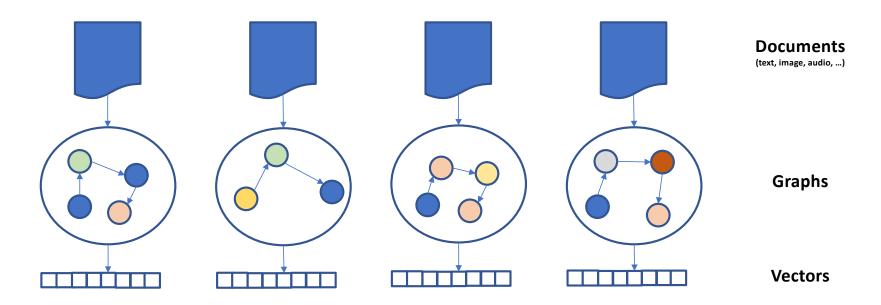


#### Solution

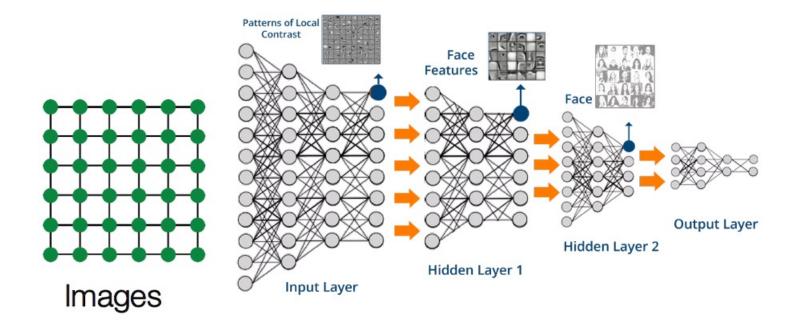
- Multi-modal information input to knowledge representation
  - Language input (speech and text)
  - Information in images
  - Haptic information
  - Secondary information: sound it makes, properties when shaking, tossing, etc.
- Graphs generated using:
  - General or common sense knowledge
  - Domain specific knowledge
  - Semantic restrictions over graphs: ontologies, taxonomies

## Document Graphs

• Concept/Knowledge Graph Document Representation

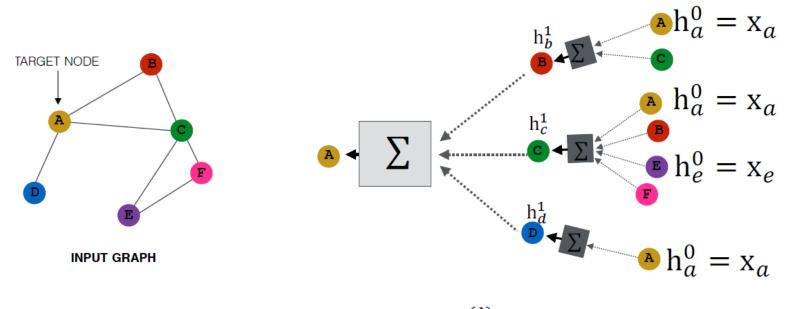


# **Graph Neural Network Models**



(C) Cavar & Dickson - ESSLLI 2024 Course

### **Graph Neural Network Models**



$$\mathbf{h}_{v}^{(l+1)} = \sigma(\mathbf{W}_{l} \sum_{u \in \mathbf{N}(v)} \frac{\mathbf{h}_{u}^{(l)}}{|\mathbf{N}(v)|} + \mathbf{B}_{l} \mathbf{h}_{v}^{(l)})$$

#### References

- Semantic Communication Enhanced by Knowledge Graph Representation Learning
  - https://arxiv.org/abs/2407.19338

### Protégé and OWL

- Download Protégé and
  - Define a simple OWL ontology
  - Reason over some asserted facts / individuals