Temporality and Affect

Natalie Parde

UIC CS 421

This Week's Topics

Tuesday

Named Entity Recognition
Information Extraction
Temporal Analysis
Affective Analysis

Thursday

(No in-person class!)
Tutorial: How to Use spaCy

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What is an entity?

- **Entities** in text are specific subjects that have been referenced
  - People
  - Locations
  - Times
  - Organizations
- Entities are typically identified and classified using a process known as **named entity recognition**

Named Entity Recognition

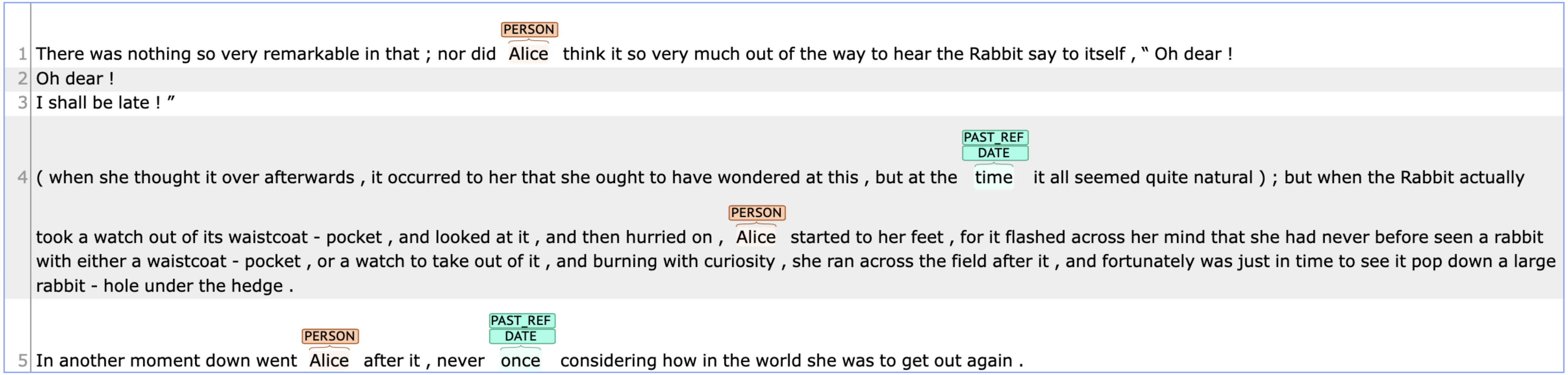
- Goal:
  1. Find spans of text that constitute proper names
  2. Tag the type of entity
- **Named entity tagsets** define the specific types of entities identified by a named entity recognizer

- Common entity tags:
  - **PER:** Person
    - People or characters
  - **LOC:** Location
    - Regions, mountains, or seas
  - **ORG:** Organization
    - Companies or sports teams
  - **GPE:** Geopolitical entity
    - Countries or states
- Entities can also include **temporal** and **numerical** expressions

Sample Named Entity Tagger Output

There was nothing so *very* remarkable in that; nor did Alice think it so *very* much out of the way to hear the Rabbit say to itself, “Oh dear! Oh dear! I shall be late!” (when she thought it over afterwards, it occurred to her that she ought to have wondered at this, but at the time it all seemed quite natural); but when the Rabbit actually *took a watch out of its waistcoat-pocket*, and looked at it, and then hurried on, Alice started to her feet, for it flashed across her mind that she had never before seen a rabbit with either a waistcoat-pocket, or a watch to take out of it, and burning with curiosity, she ran across the field after it, and fortunately was just in time to see it pop down a large rabbit-hole under the hedge.

In another moment down went Alice after it, never once considering how in the world she was to get out again.



Named entity recognition is challenging!

- Why?
  - Text segmentation can be ambiguous
    - What is part of the entity and what isn't (where are the entity's boundaries)?
  - Type determination can be ambiguous
    - Some words refer to different types of entities depending on the context

- Did [$_{Org}$ Chicago] win the game?
- I'm visiting friends in [$_{Loc}$ Chicago].
- [$_{GPE}$ Chicago] proposed a new tax ordinance.

How does named entity recognition work?

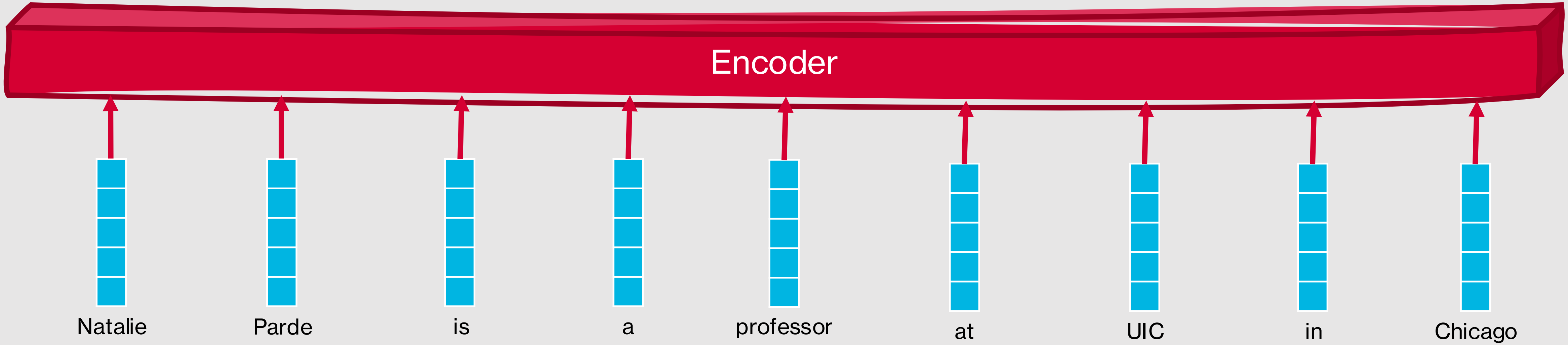
- Typically framed as a sequence labeling problem that performs span recognition
- BIO tags can be used to capture both span boundaries and named entity types

B-PER	I-PER	O	O	O	O	O	O	B-ORG	I-ORG	I-ORG	I-ORG	O	O	O	O	O	B-LOC
Natalie	Parde	is	a	faculty	member	at	the	University	of	Illinois	Chicago,	a	large	public	university	in	Chicago.

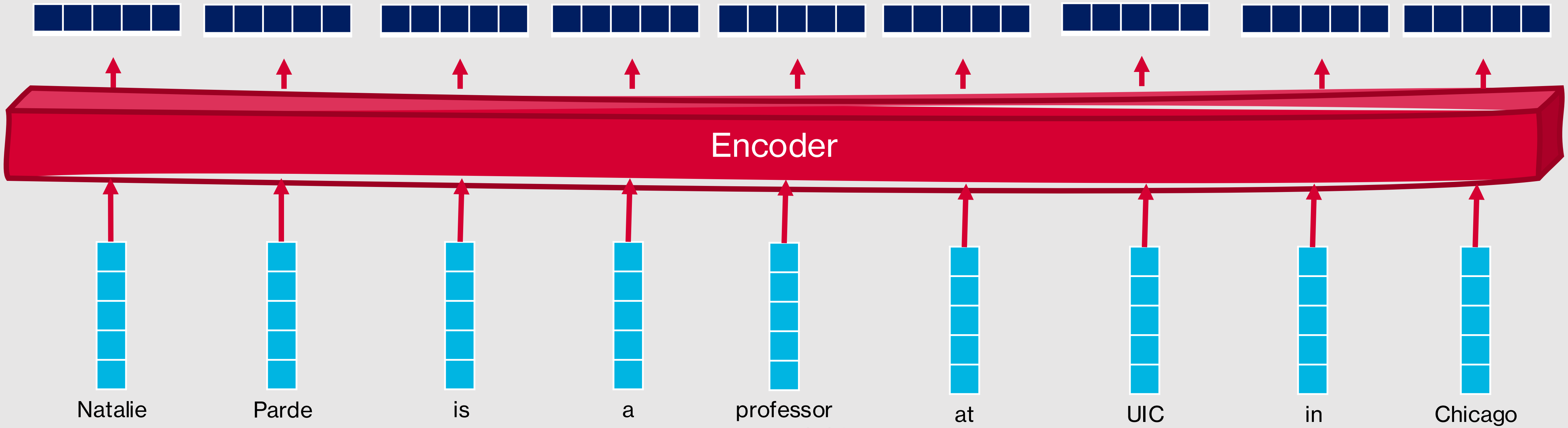
What kind of approaches do we use to implement named entity recognizers?

- Typically we will use supervised machine learning approaches to perform BIO tagging for named entity recognition
- Popular general-purpose named entity corpus:
  - **OntoNotes:** https://catalog.ldc.upenn.edu/LDC2013T19
    - Available in English, Chinese, and Arabic
- Popular biomedical named entity corpus:
  - **CRAFT:** https://github.com/UCDenver-ccp/CRAFT
- Popular literary named entity corpus:
  - **LitBank:** https://github.com/dbamman/litbank

Example Neural Named Entity Recognizer



Example Neural Named Entity Recognizer



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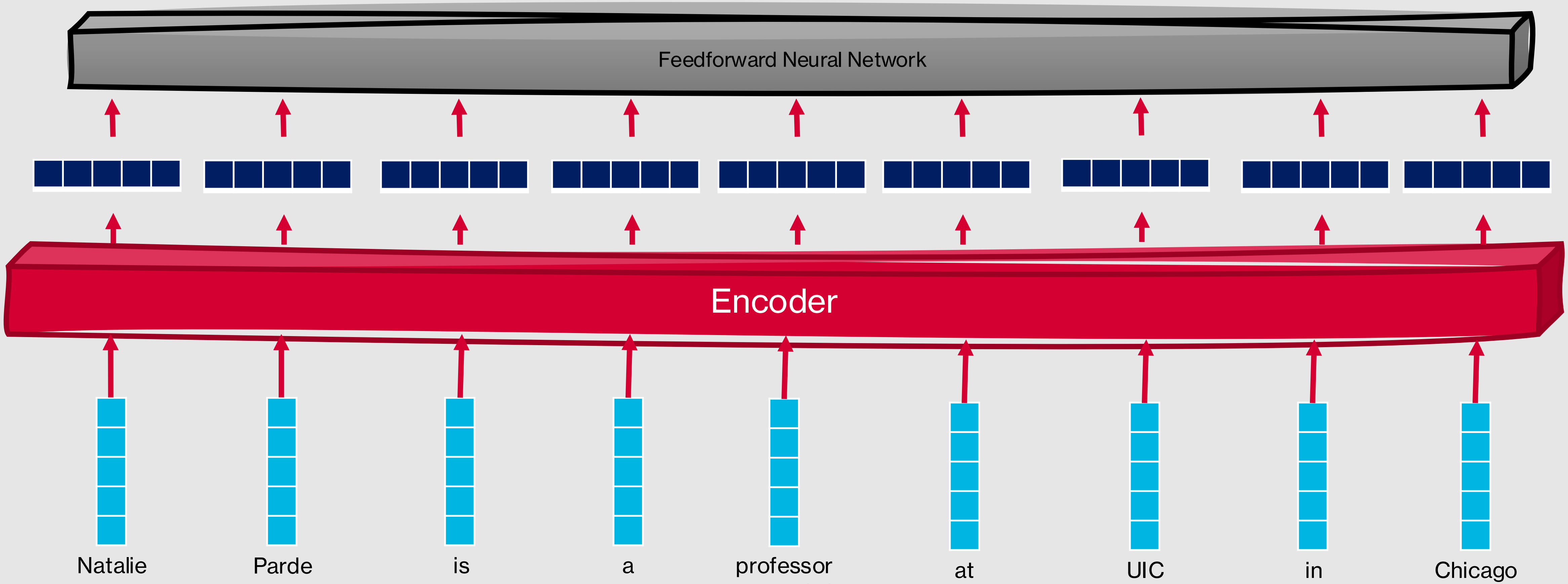
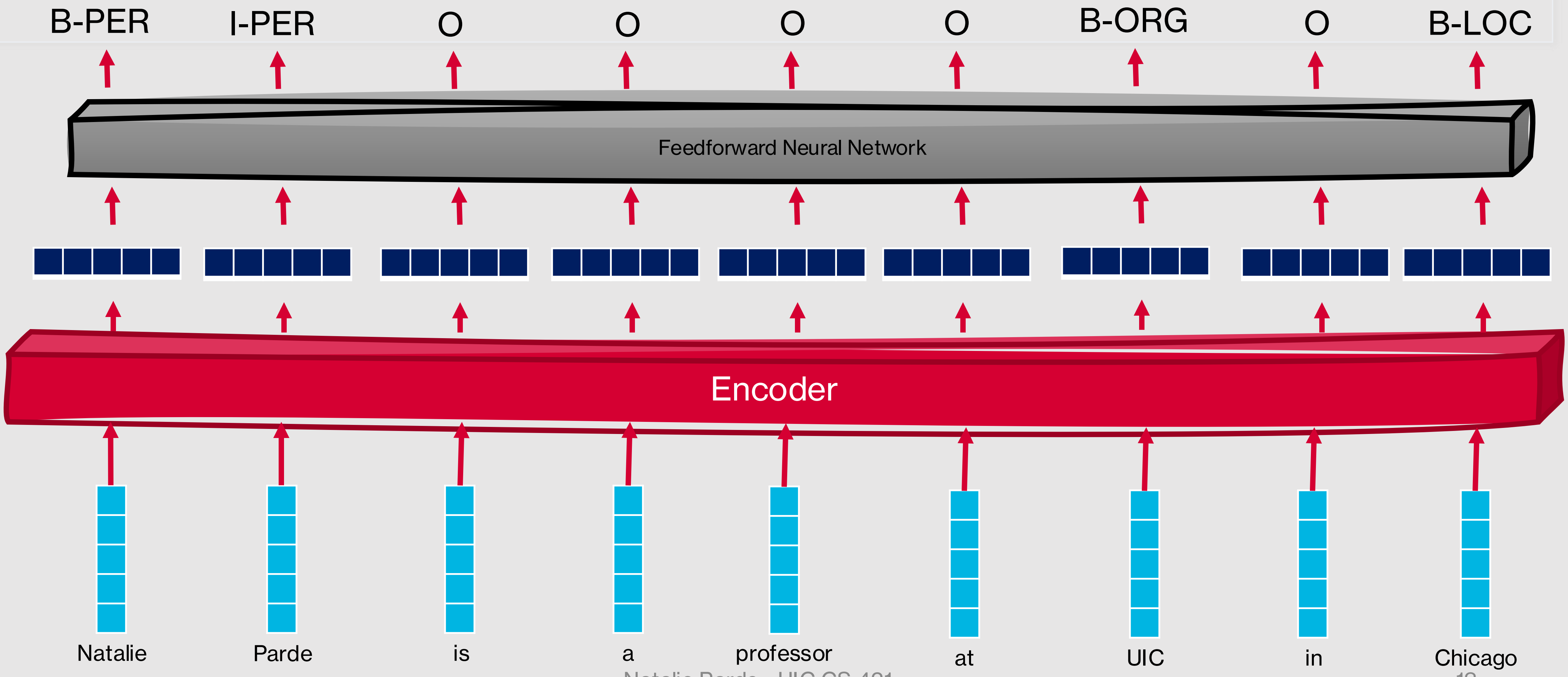


Example Neural Named Entity Recognizer



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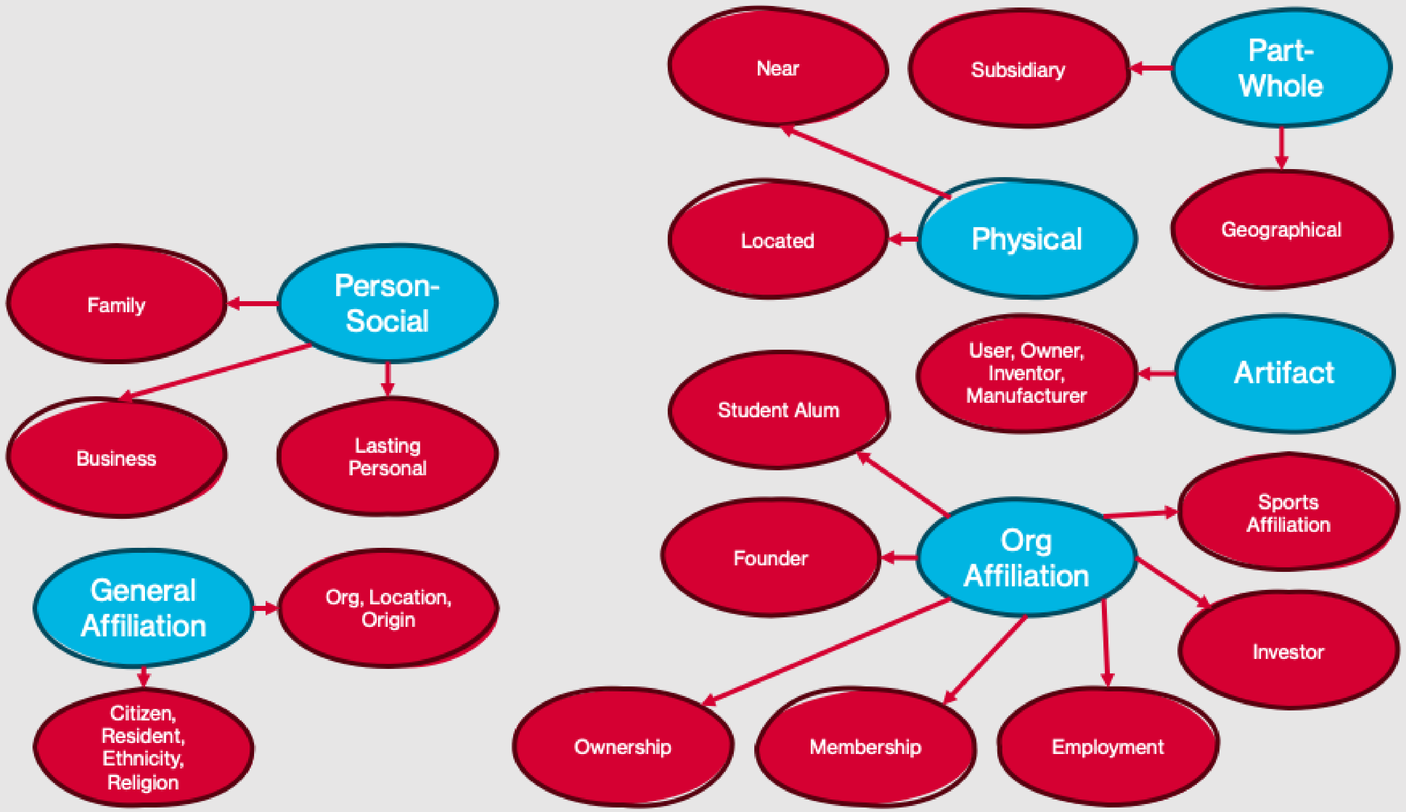
Once we've detected named entities, we can determine relationships between them.

- Numerous tagsets available
- Popular tagset: **Automatic Content Extraction (ACE) Relations**
  - 17 physical, membership, affiliation, citizenship, and discourse relations
  - Each relation links two entities



Domain-Specific Relation Sets

- For specific applications, domain-specific sets of relations may be used instead
- Popular set of entities and relations in the medical domain: **UMLS**
  - 134 broad subject categories and entity types
  - 54 relations between entities
- Browse the UMLS semantic network: https://uts.nlm.nih.gov/uts/umls/semantic-network/root

UMLS Example

Entity or event	Relation	Entity or event
Injury	Disrupts	Physiological function
Medical device	Diagnoses	Disease or syndrome
Bodily location	Location-of	Biologic function
Anatomical structure	Part-of	Organism
Pharmacologic substance	Causes	Pathological function
Pharmacologic substance	Treats	Pathologic function

Doppler echocardiography can be used to diagnose left anterior descending artery stenosis in patients with type 2 diabetes

doppler echocardiography diagnoses *acquired stenosis*

Other Sources of Relations

- Wikipedia contains structured tables associated with certain articles that can be turned into a metalanguage known as the **Resource Description Framework (RDF)**
  - RDF tripes are relationship(entity, entity) relations created using this metalanguage, which map to subject-predicate-object expressions
    - Location(Learning Center Building C, UIC)
- **DBpedia** was created from Wikipedia: https://www.dbpedia.org/
- **TACRED** contains 106,264 examples of relation triples from news and web text, with 41 relation types: https://nlp.stanford.edu/projects/tacred/
- **SemEval 2010 Task 8** dataset contains 10,717 examples of relation triples, with 9 relation types: http://www.kozareva.com/downloads.html

How can we extract relations?

- Early work searched for specific lexicosyntactic patterns, known as **Hearst patterns**
  - https://aclanthology.org/C92-2082/
- Hearst patterns can also be extended using named entity constraints

- Identifying hypernyms (NP_H)
  - NP {, NP}* {,} (and|or) other NP_H → temples, treasuries, and other important **civic buildings**
  - NP_H such as {NP,}* {(or|and)} NP → **red algae** such as Gelidium
  - such NP_H as {NP,}* {(or|and)} NP → such **authors** as Herrick, Goldsmith, and Shakespeare
  - NP_H {,} including {NP,}* {(or|and)} NP → **common-law countries**, including Canada and England
  - NP_H {,} especially {NP,}* {(or|and)} NP → **European countries**, especially France, England, and Spain
- Named entity constraints:
  - **PER**, **POSITION** of **ORG** → **George Marshall**, **Secretary of State** of **the United States**
  - **PER** (be)? ((named)|(appointed)) Prep? **ORG** **POSITION** → **George Marshall** was named **US** **Secretary of State**

Supervised Relation Extraction

- Typically requires two steps:
  1. Find all possible pairs of named entities in the text (typically restricted to the same sentence)
  2. Classify the relation for each pair (either non-existent or one of the allowable relation types)
- Optional filtering step: First make a binary decision regarding whether a given pair of entities are related in any way (and then only classify relations for those that are expected to be related)

Supervised Relation Extraction Algorithm

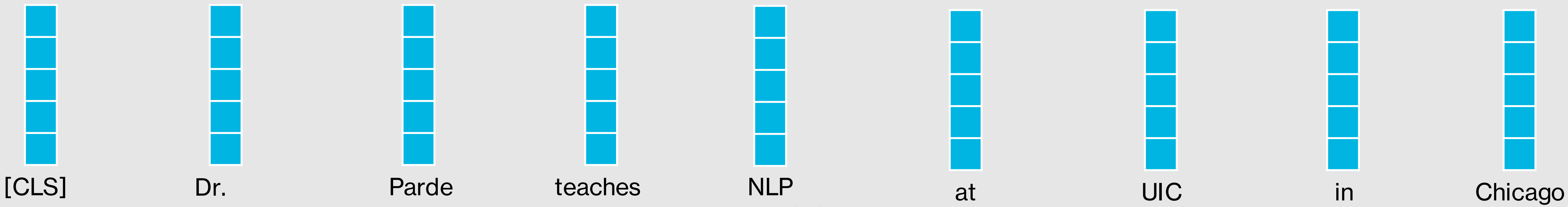
```
function FindRelations(words) returns relations

      relations ← []
      entities ← FindEntities(words)
      forall entity pairs {e1, e2} in entities do
            if Related?(e1, e2)
                  relations ← relations + ClassifyRelation(e1, e2)
      return relations
```

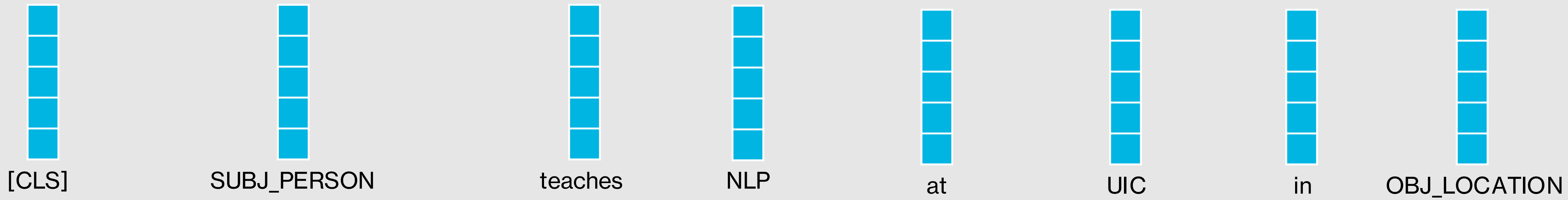
Neural Implementations

- Create a partially **delexicalized** version of the input by replacing the entities *being classified* with their named entity tags
- Finetune a pretrained model to predict the correct relation for the entities using the [CLS] token
  - Ideally, the base model should be pretrained on tasks that do not specify a sequence [SEP] token

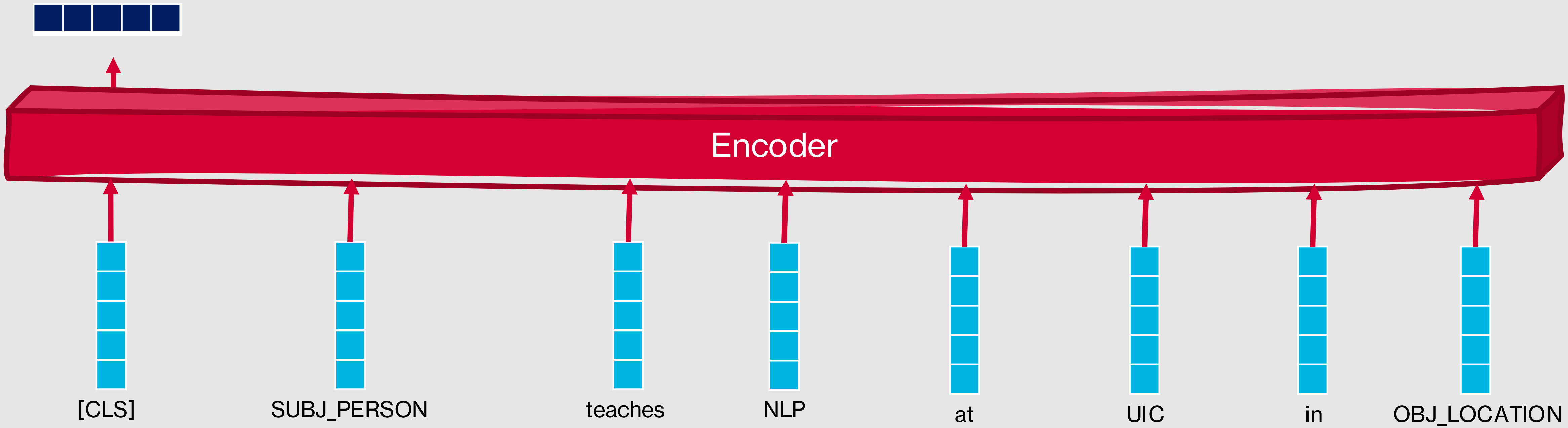
Example Neural Relation Extraction



Example Neural Relation Extraction



Example Neural Relation Extraction



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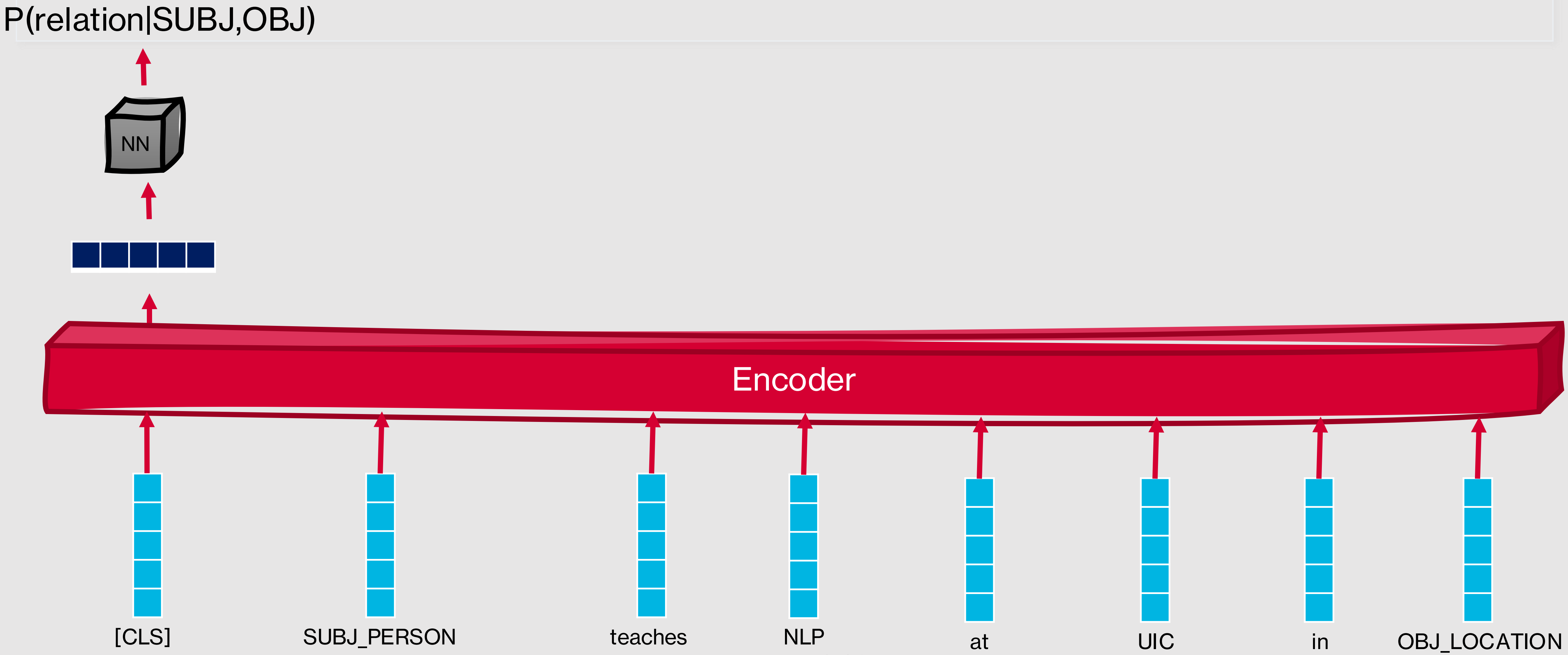

Semi-Supervised Relation Extraction

- Since building high-quality relation datasets is expensive and time-consuming, there has been substantial interest in **semi-supervised** and **unsupervised** approaches for this task
- One way to perform semi-supervised learning is by **bootstrapping** a classifier
  - Take **seed examples** and find data matching those samples in some other data source
  - Extract and generalize the context in those new samples to learn new patterns
  - Repeat
- For relation extraction, the seed examples would be seed pairs of entities

Bootstrapping Algorithm

```
function Bootstrap(Relation R) returns new relation tuples

        tuples ← Gather a set of seed tuples that have relation R
        iterate
                sentences ← Find sentences that contain entities in tuples
                patterns ← Generalize the context between and around entities in sentences
                newpairs ← Use patterns to identify more tuples
                newpairs ← newpairs with high confidence
                tuples ← tuples + newpairs
        return tuples
```

Distant Supervision for Relation Extraction

- Another way to avoid expensive manual labeling of relation labels is to perform **distant supervision** with indirect sources of training data
- Combines advantages of bootstrapping and supervised learning by:
  - Using a large database to acquire many seed examples
  - Create many noisy pattern features from these examples
  - Combine these in a supervised classifier

Distant Supervision Algorithm

```
function DistantSupervision(Database D, Text T) returns relation classifier C
        observations = []
        foreach relation R in D
                foreach tuple (e1, e2) of entities with relation R
                        sentences ← Sentences in T that contain e1 and e2
                        f ← Frequent features in sentences
                        observations ← observations + new training tuple (e1, e2, f, R)
        C ← Train supervised classifier on observations
        return C
```

Unsupervised Relation Extraction

- Uses in situations with no labeled training data, such as when you are working with:
  - Low-resource domains
  - New domains
- Often referred to as **open information extraction (Open IE)**
- Relations are generally strings of words, rather than more formal relations

How does open information extraction work?

1. Run a part-of-speech tagger and named entity recognizer over the sentence
2. For each verb in that sentence, find the longest sequence of words *w* that starts with a verb and satisfies any specified syntactic and lexical constraints
3. For each retrieved sequence of words, find the nearest noun phrase *x* prior to the sequence that is not a relative pronoun, wh-word, or existential "there"
4. Likewise, find the nearest noun phrase *y* after the sequence
5. Assign a confidence *c* to the relation $r = (x, w, y)$ using a confidence classifier

Evaluating Methods for Relation Extraction

- Supervised relation extraction systems can be evaluated using standard NLP metrics (e.g., precision, recall, and F-measure)
- Semi-supervised and unsupervised relation extraction systems are more challenging to evaluate since there is typically not an existing gold standard for comparison

Evaluating Semi-Supervised and Unsupervised Systems

- **Approximate precision** by randomly sampling output relations and asking a human to manually evaluate them
  - $\hat{P} = \frac{\text{\# correctly extracted relation tuples in the sample}}{\text{\# extracted relation tuples in the sample}}$
- **Approximate recall** by computing precision at different sample sizes
  - Precision for most-confident 1000 new relations
  - Precision for most-confident 10,000 new relations
  - And so forth!

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Event Extraction

- **The process of finding events in which entities in the text participate**
- In general, event extractors are designed to classify events based on their aspectual and temporal properties

What is an event mention?

Any expression denoting an event or state that can be assigned to a particular point or interval in time

Most event mentions in English correspond to verbs (and most English verbs introduce events) although this is not a requirement

[EVENT Citing] high fuel prices, United Airlines **[EVENT said]** Friday it has **[EVENT increased]** fares by $6 per round trip on flights to some cities also served by lower-cost carriers. American Airlines, a unit of AMR Corp., immediately **[EVENT matched]** **[EVENT the move]**, spokesman Tim Wagner **[EVENT said]**. United, a unit of UAL Corp., **[EVENT said]** **[EVENT the increase]** took effect Thursday and **[EVENT applies]** to most routes where it **[EVENT competes]** against discount carriers, such as Chicago to Dallas and Denver to San Francisco.

Event Extraction Datasets

- Typically also include annotations for temporal and aspectual information
- TempEval Shared Tasks:
  - https://aclweb.org/aclwiki/Temporal_Information_Extraction_(State_of_the_art)
  - https://alt.qcri.org/semeval2017/task12/

[EVENT **Citing**] high fuel prices, United Airlines [EVENT **said**] Friday it has [EVENT **increased**] fares by $6 per round trip on flights to some cities also served by lower-cost carriers. American Airlines, a unit of AMR Corp., immediately [EVENT **matched**] [EVENT **the move**], spokesman Tim Wagner [EVENT **said**]. United, a unit of UAL Corp., [EVENT **said**] [EVENT **the increase**] took effect Thursday and [EVENT **applies**] to most routes where it [EVENT **competes**] against discount carriers, such as Chicago to Dallas and Denver to San Francisco.

said(class=reporting, tense=past, aspect=perfective)

Event Extraction Approaches

- Generally framed as a supervised sequence labeling problem
- BIO tags are used to assign event classes and attributes
- Many events correspond to fairly common, stereotypical situations in the world
  - **Scripts** are prototypical sequences of sub-events, participants, and their roles
  - We can represent scripts using simple **templates**

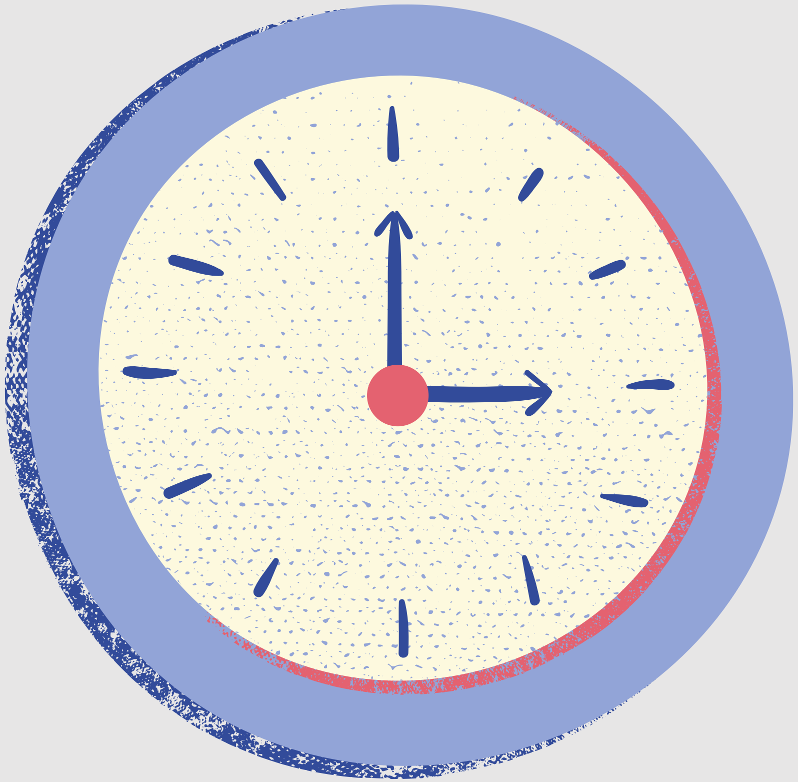
Citing high fuel prices, United Airlines said Friday it has increased fares by $6 per round trip on flights to some cities also served by lower-cost carriers. American Airlines, a unit of AMR Corp., immediately matched the move, spokesman Tim Wagner said. United, a unit of UAL Corp., said the increase took effect Thursday and applies to most routes where it competes against discount carriers, such as Chicago to Dallas and Denver to San Francisco.

Fair-Raise Attempt:

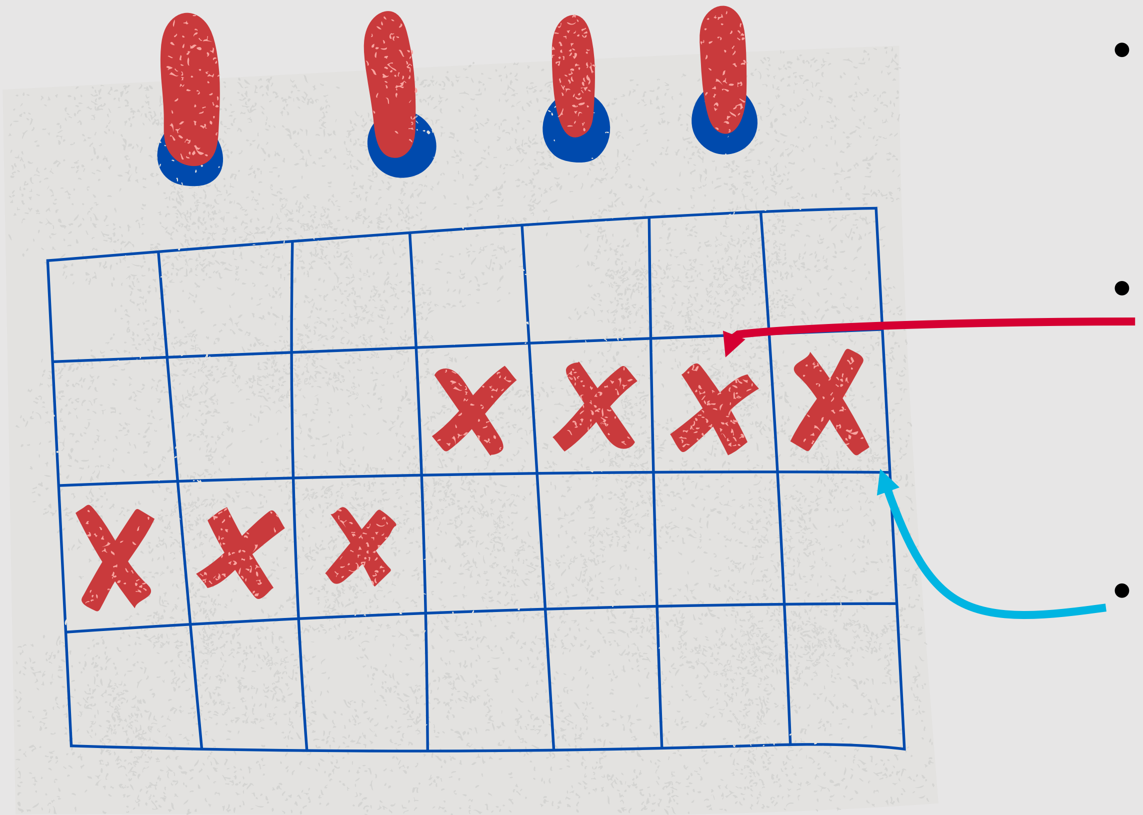
• Lead Airline:	United Airlines
• Amount:	$6
• Effective Date:	2006-10-26
• Follower:	American Airlines

Time and Temporality

- Events are situated within time, and they can also relate to one another temporally
  - Events happen at particular dates and times
  - Events can occur before, after, or simultaneously with one another



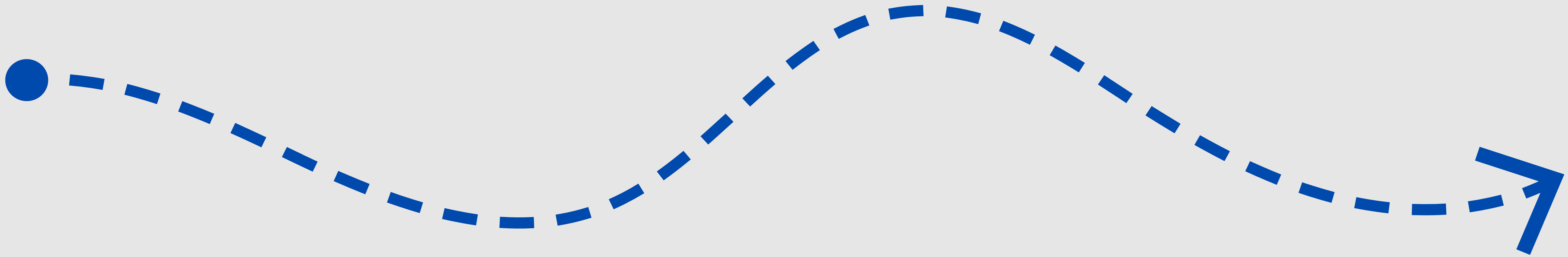
Temporal Expressions



- Temporal expressions allow us to understand how events are situated within time
- These expressions may be explicit statements of date or time:
  - Assignment 4 is due two Fridays from now at 12 p.m.
- Or they may be in reference to other expressions or events:
  - 26 hours from now

Representing Time

- Although there are numerous philosophical theories of time, the most straightforward theory holds that:
  - **Time flows forward**
  - **Events are associated with points or intervals in time**
- Assuming this to be true, we can order events by situating them on a timeline, with one event preceding another if time flows from the first event to the second
- If we situate the current moment in time along this timeline, we build notions of past, present, and future
- **Temporal logic** is a formal way to represent temporal information, typically within the first-order logic framework



How do we adapt first-order logic to represent temporality?

- Simple first-order logic representations focus on meaning irrespective of time

$$\exists e\ \mathrm{Arriving}(e) \land \mathrm{Arriver}(e, \mathrm{Speaker}) \land \mathrm{Destination}(e, \mathrm{Chicago})$$

I arrived in Chicago.

I am arriving in Chicago.

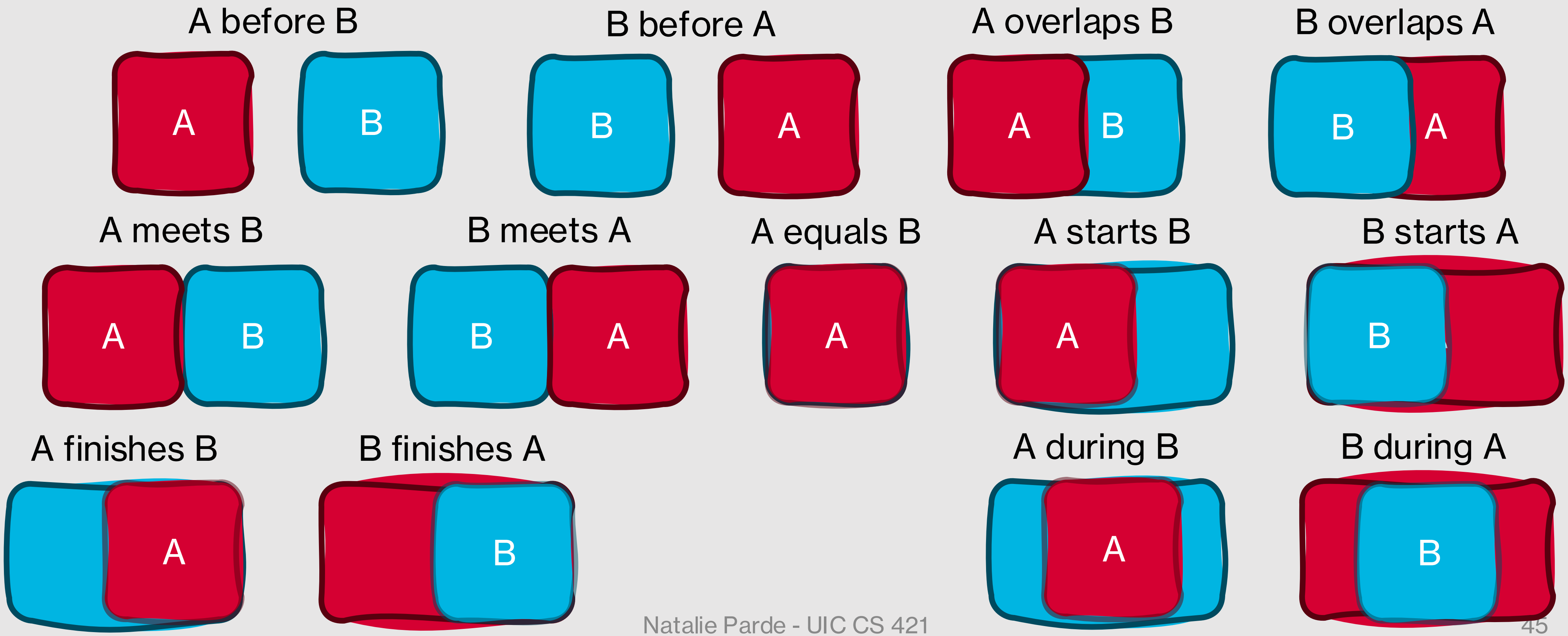
I will arrive in Chicago.

How do we adapt first-order logic to represent temporality?

- Specify temporal information based on the event's order with respect to other events using attributes of the **event variable**
  - **Interval algebra** is one framework developed by James F. Allen that is used to discuss temporal ordering relationships
    - All events and time expressions are modeled as intervals (no time points!), which can be long or very short

Allen Relations

- There are 13 relations that can hold between intervals A and B in interval algebra



Interval Algebra in Practice

Original First-Order Logic

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Interval Algebra in Practice

Updated First-Order Logic

Original First-Order Logic

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I am arriving in Chicago.

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$$\exists e, i \ \text{Arriving}(e) \land \text{Arriver}(e, \text{Speaker}) \land \text{Destination}(e, \text{Chicago}) \land \text{IntervalOf}(e, i) \land \text{Before}(i, \text{Now})$$

Interval Algebra in Practice

Updated First-Order Logic

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Interval Algebra in Practice

Updated First-Order Logic

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$\exists e, i\ \text{Arriving}(e) \wedge \text{Arriver}(e, \text{Speaker}) \wedge \text{Destination}(e, \text{Chicago}) \wedge \text{IntervalOf}(e, i) \wedge \text{After}(i, \text{Now})$

Temporal Ambiguity

- Although relating verb tenses with points in time may initially seem simple, there are many opportunities for ambiguity to arise
  - *Okay, we fly from Chicago to Burlington at noon.*
    - Present tense verb indicating future event
  - *Flight 1902 had arrived late.*
    - Past tense verb with respect to some unnamed event.
- To address this, Hans Reichenbach introduced the notion of reference points that are separate from the utterance time and event time
  - Reichenbach, Hans (1947). *Elements of Symbolic Logic*. New York: Macmillan & Co.

Reichenbach's Reference Point

When I got off the blue line, I taught CS 421.

Happened before the utterance

When I got off the blue line, I had taught CS 421.

Reichenbach's Reference Point

Reference point

When I got off the blue line, I taught CS 421.

Happened before the utterance

Reference point

When I got off the blue line, I had taught CS 421.

Reichenbach's Reference Point

Reference point

When I got off the blue line, I taught CS 421.

Happened before the utterance

Happened *after* the speaker got off the blue line

Reference point

When I got off the blue line, I had taught CS 421.

Happened *prior to* when the speaker got off the blue line

Reichenbach's Reference Point

Reference point

When I got off the blue line, I taught CS 421.

Happened before the utterance

Happened *after* the speaker got off the blue line

- Reference point precedes the teaching event

Reference point

When I got off the blue line, I had taught CS 421.

Happened *prior to* when the speaker got off the blue line

- Teaching event precedes the reference point

Time and Metaphor

- Many languages (including English) frequently rely on **metaphors** to express temporality
- Most frequent in English: <TIME> is <SPACE>
  - *In* the morning
  - *Around* noon
  - Midnight is *near*
- This facilitates understanding of a complex topic for humans, but may create additional complexities when processing temporal expressions computationally

Aspect

- **Aspect** defines categories of events or states based on their temporal structure
- Events may be:
  - Ongoing or complete
  - At a specific point or over an interval of time

Aspectual Distinctions

- **Events** involve change, whereas **states** do not
- **Stative expressions** indicate the state or property of an event participant at a given point in time

I **like** CS 421.

I **need** to finish my research project.

I **want** to take CS 521.

- Event participant is experiencing something at a specific point in time
- Event doesn't involve internal change over time

Aspectual Distinctions

Activit
y

Souvik lives in Chicago.

Natalie works at UIC.

- Event participant is or has engaged in the activity for some period of time
- No specification that the activity might have stopped

Accomplishment

Abari ordered some ice cream.

Meghan traveled to New Orleans.

- Event occurs over some period of time
- Event ends when the intended state is accomplished

Achievement

Eli found the missing assignment.

Gyeongeun finished the paper.

- Event occurs in an instant
- Event results in a new state

Event expressions can easily be shifted to other aspectual classes!

- Surrounding context guides the interpretation of the event

Mina sailed. → Mina sailed to Paris.

Activity → Accomplishment

TimeBank

- Popular dataset for this domain
  - American English text annotated using **TimeML**, a markup language based on interval algebra
  - TimeML includes three types of objects:
    - **Events** (representing events and states)
    - **Times** (representing temporal expressions like dates)
    - **Links** (representing relationships between events and times)
      - **TLinks** describe Allen relations
      - **ALinks** describe aspectual relationships
      - **SLinks** describe subordination relationships involving modality, evidentiality, and factuality
  - More details: https://timeml.github.io/site/timebank/documentation-1.2.html

TimeBank

Delta Air Lines earnings soared 33% to a record in the fiscal first quarter, bucking the industry trend toward declining profits.

<TIMEX3 tid=“t57” type=“DATE” value=“1989-10-26” functionInDocument=“CREATION_TIME”> 10/26/89 </TIMEX3>

Delta Air Lines earnings <EVENT eid=“e1” class=“OCCURRENCE”> soared </EVENT> 33% to a record in <TIMEX tid==“t58” type=“DATE” value=“1989-Q1” anchorTimeID=“t57”> the fiscal first quarter </TIMEX3>, <EVENT eid=“e3” class=“OCCURRENCE”>bucking</EVENT> the industry trend toward <EVENT eid=“e4” class=“OCCURRENCE”>declining</EVENT> profits.

TimeBank

Delta Air Lines earnings soared 33% to a record in the fiscal first quarter, bucking the industry trend toward declining profits.

- Three events

```
<TIMEX3 tid=“t57” type=“DATE” value=“1989-10-26” functionInDocument=“CREATION_TIME”>
10/26/89 </TIMEX3>

Delta Air Lines earnings <EVENT eid=“e1” class=“OCCURRENCE”> soared </EVENT> 33% to a
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industry trend toward <EVENT eid=“e4” class=“OCCURRENCE”>declining</EVENT> profits.
```

TimeBank

Delta Air Lines earnings soared 33% to a record in the fiscal first quarter, bucking the industry trend toward declining profits.

- Three events
- Two temporal expressions

<TIMEX3 tid="t57" type="DATE" value="1989-10-26" functionInDocument="CREATION_TIME"> 10/26/89 </TIMEX3>

Delta Air Lines earnings <EVENT eid="e1" class="OCCURRENCE"> soared </EVENT> 33% to a record in <TIMEX tid="t58" type="DATE" value="1989-Q1" anchorTimeID="t57"> the fiscal first quarter </TIMEX3>, <EVENT eid="e3" class="OCCURRENCE">bucking</EVENT> the industry trend toward <EVENT eid="e4" class="OCCURRENCE">declining</EVENT> profits.

TimeBank

Delta Air Lines earnings soared 33% to a record in the fiscal first quarter, bucking the industry trend toward declining profits.

- Three events
- Two temporal expressions
- Four temporal links capturing Allen relations

```
<TIMEX3 tid=“t57” type=“DATE” value=“1989-10-26” functionInDocument=“CREATION_TIME”>
10/26/89 </TIMEX3>

Delta Air Lines earnings <EVENT eid=“e1” class=“OCCURRENCE”> soared </EVENT> 33% to a
record in <TIMEX3 tid=“t58” type=“DATE” value=“1989-Q1” anchorTimeID=“t57”> the fiscal
first quarter </TIMEX3>, <EVENT eid=“e3” class=“OCCURRENCE”>bucking</EVENT> the industry
trend toward <EVENT eid=“e4” class=“OCCURRENCE”>declining</EVENT> profits.

<TLINK lid=“l1” relType=“IS_INCLUDED” eventInstanceID=“e1” relatedToTime=“t58” />
<TLINK lid=“l2” relType=“BEFORE” eventInstanceID=“e1” relatedToTime=“t57” />
<TLINK lid=“l3” relType=“SIMULTANEOUS” eventInstanceID=“e1” relatedToEventInstance=“e3” />
<TLINK lid=“l4” relType=“IS_INCLUDED” eventInstanceID=“e1” relatedToEventInstance=“e4” />
```

How can we automatically recognize and interpret the types of information present in TimeBank?

- Automated **temporal analysis** involves three common steps:
  - **Extracting temporal expressions**
  - **Normalizing these expressions** by converting them to a standard format
  - **Linking events to times** and **extracting time graphs and timelines** from the text

Extracting Temporal Expressions

- **Absolute temporal expressions** can be mapped directly to calendar dates, times of day, or both
- **Relative temporal expressions** can be mapped to particular times through some other reference point
  - *A week from last Tuesday*
- **Durations** can be mapped to spans of time at varying levels of granularity
  - Seconds, minutes, days, weeks, years, etc.

Absolute	Relative	Duration
October 31, 2025	Yesterday	Two hours
The summer of 2025	Next semester	Three days
9:30 a.m.	Two weeks from yesterday	Four years
The fall semester in 2025	Last year	Two semesters

Temporal Normalization

- Once we recognize temporal expressions, we can **normalize** them by mapping them to specific durations or points in time
- Normalized times are represented using the **ISO 8601** standard for encoding temporal values
  - **Date:** YYYY-MM-DD
  - **Weeks:** YYYY-W*nn*, with weeks numbered from 01-53 in the year (W001 has the first Thursday of the year)
    - Note: ISO weeks begin on Monday
  - **Durations:** P*nx*, where *n* denotes the length as an integer and *x* represents the temporal unit of measurement (e.g., P3Y="three years" or P2D="two days")

```
<TIMEX3 tid="t57" type="DATE" value="1989-10-26" functionInDocument="CREATION_TIME"> 10/26/89 </TIMEX3>

Delta Air Lines earnings <EVENT eid="e1" class="OCCURRENCE"> soared </EVENT> 33% to a record in <TIMEX3 tid="t58"
type="DATE" value="1989-Q1" anchorTimeID="t57"> the fiscal first quarter </TIMEX3>, <EVENT eid="e3"
class="OCCURRENCE">bucking</EVENT> the industry trend toward <EVENT eid="e4" class="OCCURRENCE">declining</EVENT>
profits.

<TLINK lid="l1" relType="IS_INCLUDED" eventInstanceID="e1" relatedToTime="t58" />
<TLINK lid="l2" relType="BEFORE" eventInstanceID="e1" relatedToTime="t57" />
<TLINK lid="l3" relType="SIMULTANEOUS" eventInstanceID="e1" relatedToEventInstance="e3" />
<TLINK lid="l4" relType="IS_INCLUDED" eventInstanceID="e1" relatedToEventInstance="e4" />
```

Sample ISO Patterns for Times and Durations

Unit	Pattern	Sample Value
Fully specified dates	YYYY-MM-DD	2024-10-31
Weeks	YYYY-Wnn	2024-W10
Weekends	PnWE	P1WE
24-hour clock times	HH:MM:SS	09:30:00
Dates and times	YYYY-MM-DDTHH:MM:SS	2024-10-31T09:30:00

Additional Examples: https://en.wikipedia.org/wiki/ISO_8601

How can we perform temporal normalization?

- Temporal normalization is often handled using rule-based approaches that match patterns associated with different types of temporal expressions

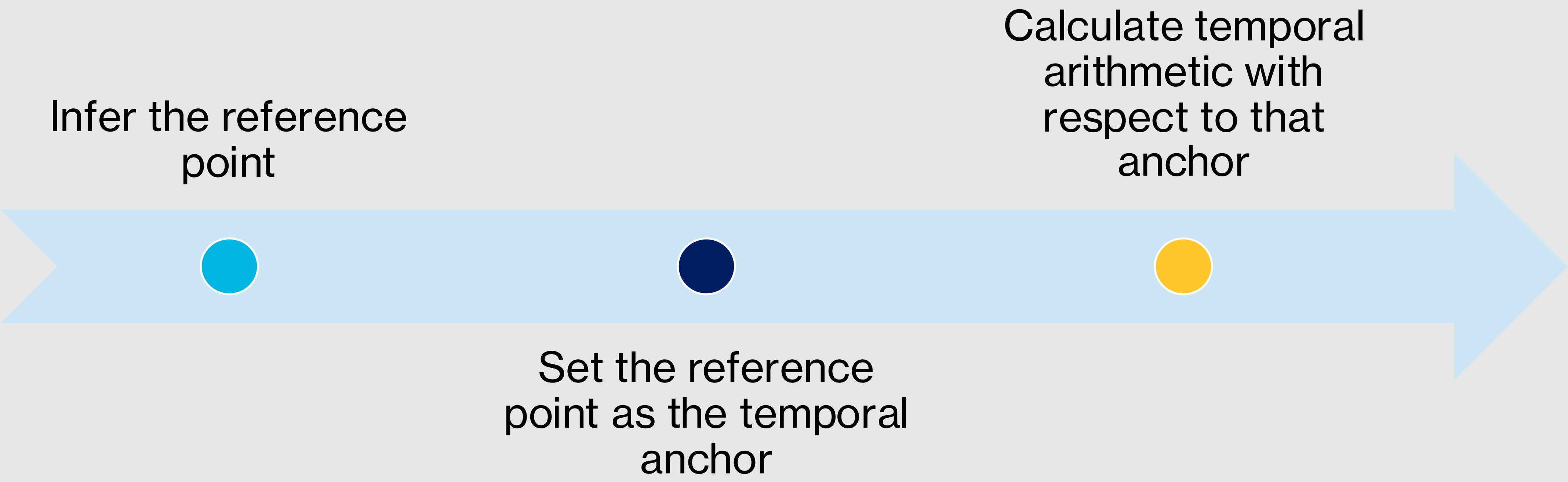
```
Pattern: /(\d+)[-\s]($TEUnits)(s)?([-\s]old)?/
Result:  Duration($1, $2)
```

- This is challenging because:
  - Fully qualified temporal expressions tend to be rare
  - Most expressions in text instead do not explicitly state a **temporal anchor**

Temporal Anchors

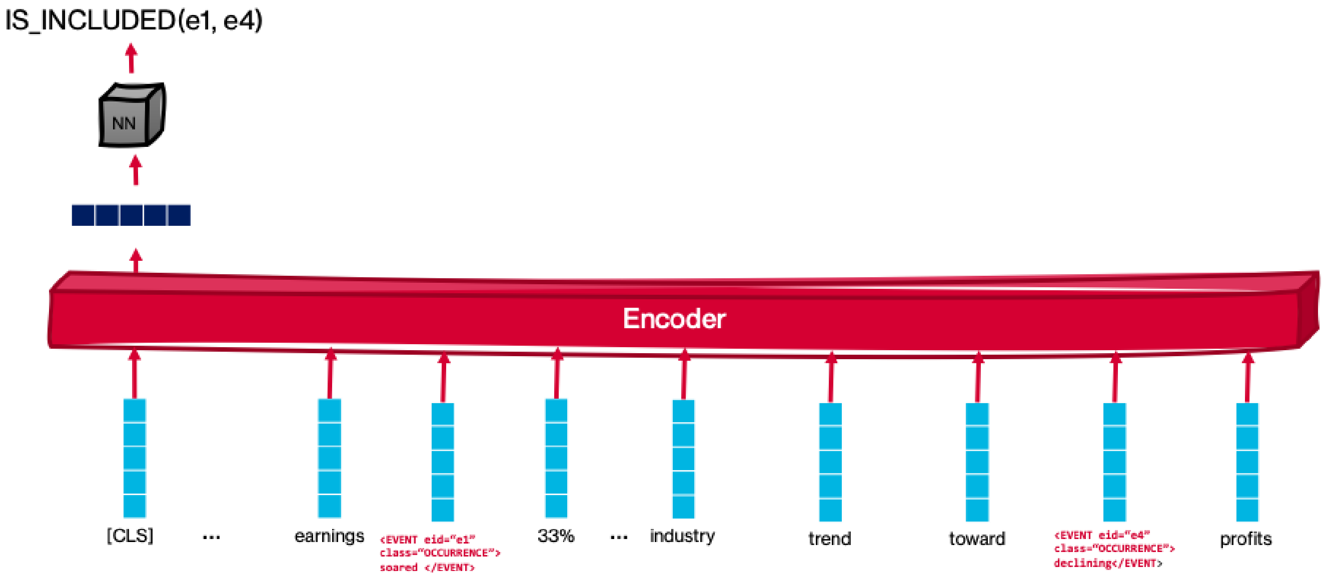
- Temporal anchors serve as the base point across which temporal expressions are normalized
  - "Today" = temporal anchor
  - "Yesterday" = temporal anchor – 1
  - "Tomorrow" = temporal anchor + 1
- **Without an explicit temporal anchor, we must infer the temporal anchor implicitly** (generally using domain-specific heuristics)
  - News articles: The temporal anchor can generally assumed to be the dateline for the news article

Relative Temporal Expressions



Temporal Ordering of Events

- The broader goal of extracting and normalizing temporal expressions is to be able to situate them along a timeline
- One step toward achieving this goal is to perform **temporal ordering**, such that extracted events are ordered based on the resolved temporal expressions within the text
  - Detect all events and temporal expressions from the text
  - For all possible event-event, event-time, and time-time pairs, assert links
    - Train temporal relation classifiers to predict TLinks



This Week's Topics

Named Entity Recognition
Information Extraction
Temporal Analysis
Affective Analysis

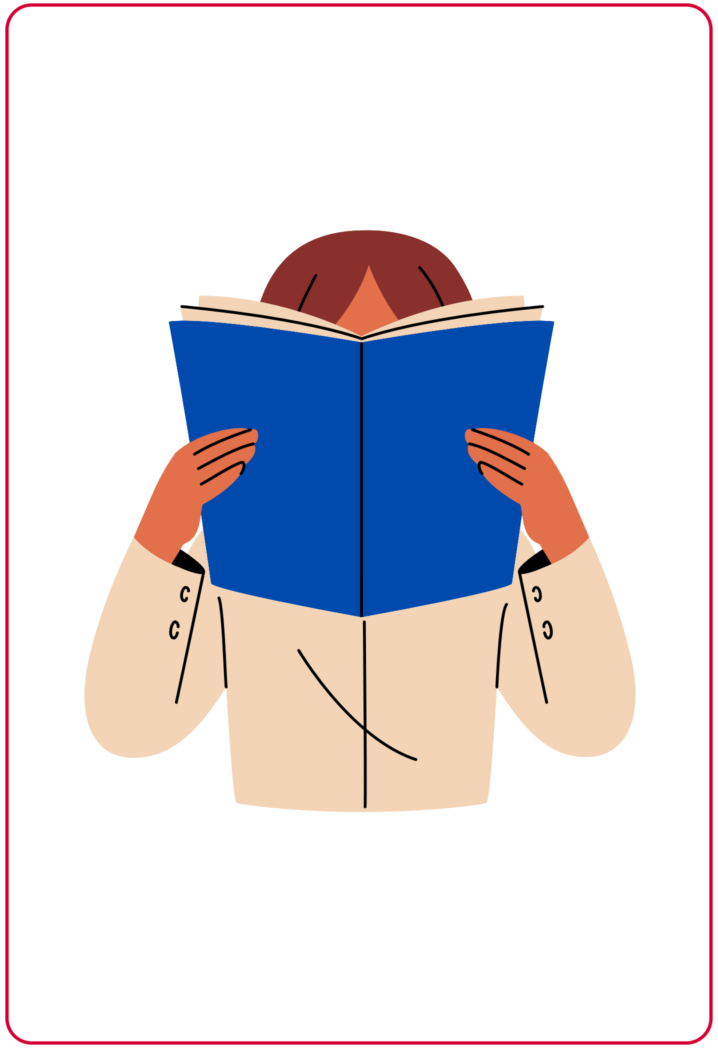
Tuesday

Thursday

(No in-person class!)
Tutorial: How to Use spaCy

Affective Analysis

- The automated analysis of the **emotions**, **moods**, **attitudes**, **stance**, or **personality** that is conveyed or evoked by a language sample
- Popular tool to facilitate social science research
  - Determining views towards a specific topic
  - Assessing public opinion
  - Interpreting intent



What are some common forms of affective analysis?

SENTIMENT ANALYSIS

EMOTION RECOGNITION

CONNOTATION FRAMING

Emotion Recognition

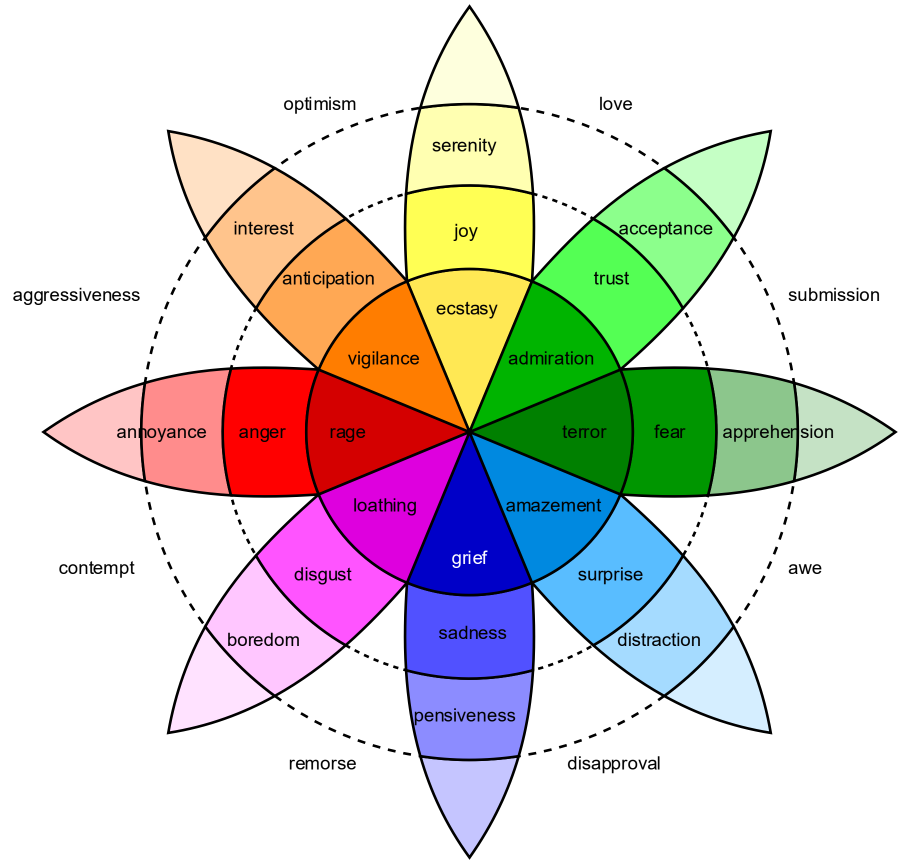
- Emotion can be defined in numerous ways
- In some frameworks, emotion is an **atomic unit**
  - IsHappy = TRUE
- In other frameworks, emotion is a **point along a multi-dimensional continuum**
  - Happiness = 0.78
- Common emotion frameworks:
  - Ekman’s six basic emotions
  - Plutchik’s wheel of emotion

Ekman's Basic Emotions

- Paper:
  - Ekman, P. (1999). Basic emotions. In T. Dalgleish & M. J. Power (Eds.), Handbook of cognition and emotion (pp. 45–60). John Wiley & Sons Ltd. https://doi.org/10.1002/0470013494.ch3
- Six basic emotions:
  - Happiness
  - Sadness
  - Anger
  - Fear
  - Disgust
  - Surprise
- Emotions are distinct from one another
- Generally known to be present across cultures

Plutchik Wheel of Emotion

- Paper:
  - Plutchik, R. (1980). A general psychoevolutionary theory of emotion. In *Theories of emotion* (pp. 3-33). Academic press. https://doi.org/10.1016/B978-0-12-558701-3.50007-7
- Situates eight basic emotions in a wheel
- Emotions located opposite one another also oppose one another semantically
- Stronger emotions derived from the basic emotions are located at more internal locations
- Weaker emotions derived from the basic emotions are located at more external locations



Atomic vs. Continuous Emotions

- Ekman and Plutchik both define emotion as an atomic unit
- Emotion along a continuum is often represented using a set of common dimensions
  - **Valence:** Pleasantness (e.g., positive or negative)
  - **Arousal:** Intensity of emotion provoked (e.g., strong or weak)
  - (Sometimes) **Dominance:** Degree of control exerted (e.g., active or passive)
- Sentiment is sometimes viewed as a measure of valence

Sentiment and Affect Lexicons

- A wide range of resources for sentiment and affect recognition are available for public use!
- These are useful for performing automated sentiment or affect analysis

MPQA Subjectivity Lexicon

- Collection of positive and negative words from existing lexicons
  - 2718 positive words
  - 4912 negative words
- Additional subjective words learned via bootstrapping, with manually-provided sentiment and subjectivity levels
  - Wilson, T., Wiebe, J., & Hoffmann, P. (2005). Recognizing contextual polarity in phrase-level sentiment analysis. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (pp. 347-354).
- Link:
  - https://mpqa.cs.pitt.edu/lexicons/subj_lexicon/

Opinion Lexicon

- Positive and negative words collected from product reviews via bootstrapping
  - Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 168-177).
- 2006 positive words
- 4783 negative words
- Link:
  - https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

VAD Lexicon Scores

- 20,000 words labeled with valence, arousal, and dominance scores
  - Mohammad, S. (2018a). Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 english words. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics* (pp. 174-184).
- Link: https://saifmohammad.com/WebPages/nrc-vad.html
- Translations are available in 100+ languages

The NRC VAD Lexicon

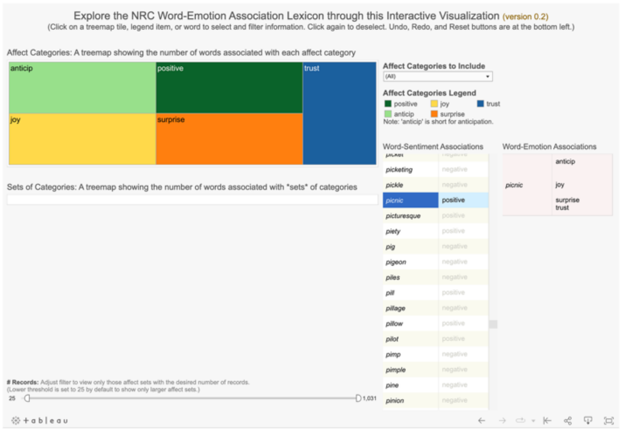
term	valence	arousal	dominance
aaaaaaah	0.479	0.606	0.291
aaaah	0.520	0.636	0.282
aardvark	0.427	0.490	0.437
aback	0.385	0.407	0.288
abacus	0.510	0.276	0.485
abalone	0.500	0.480	0.412
abandon	0.052	0.519	0.245
abandoned	0.046	0.481	0.130
abandonment	0.128	0.430	0.202
abashed	0.177	0.644	0.307
abate	0.255	0.696	0.604
abatement	0.388	0.338	0.336

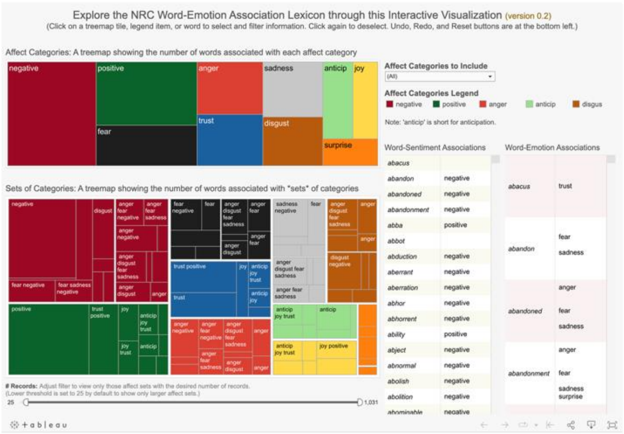
Most extreme scores for each dimension:

Dimension	Word	Score ↑	Word	Score ↓
valence	love	1.000	toxic	0.008
arousal	abduction	0.990	mellow	0.069
dominance	powerful	0.991	empty	0.081

NRC Word-Emotion Association Lexicon

- Approximately 14,000 words labeled for the eight basic emotions from Plutchik's wheel of emotions
  - Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. *Computational Intelligence*, 29(3), 436-465.
- Link:
  - https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm





NRC Emotion Intensity Lexicon

- Approximately 10,000 words labeled with continuous scores for the eight basic emotions from Plutchik's wheel of emotions
  - Mohammad, S. (2018b). Word Affect Intensities. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*.
- Link:
  - https://www.saifmohammad.com/WebPages/AffectIntensity.htm

Word	Anger	Word	Fear	Word	Joy	Word	Sadness
outraged	0.964	*horror*	0.923	*sohappy*	0.868	*sad*	0.844
brutality	0.959	*horrified*	0.922	*superb*	0.864	*suffering*	0.844
satanic	0.828	*hellish*	0.828	*cheered*	0.773	*guilt*	0.750
hate	0.828	*grenade*	0.828	*positivity*	0.773	*incest*	0.750
violence	0.742	*strangle*	0.750	*merrychristmas*	0.712	*accursed*	0.697
molestation	0.742	*tragedies*	0.750	*bestfeeling*	0.712	*widow*	0.697
volatility	0.687	*anguish*	0.703	*complement*	0.647	*infertility*	0.641
eradication	0.685	*grisly*	0.703	*affection*	0.647	*drown*	0.641
cheat	0.630	*cutthroat*	0.664	*exalted*	0.591	*crumbling*	0.594
agitated	0.630	*pandemic*	0.664	*woot*	0.588	*deportation*	0.594
defiant	0.578	*smuggler*	0.625	*money*	0.531	*isolated*	0.547
coup	0.578	*pestilence*	0.625	*rainbow*	0.531	*unkind*	0.547
overbearing	0.547	*convict*	0.594	*health*	0.493	*chronic*	0.500
deceive	0.547	*rot*	0.594	*liberty*	0.486	*injurious*	0.500
unleash	0.515	*turbulence*	0.562	*present*	0.441	*memorials*	0.453
bile	0.515	*grave*	0.562	*tender*	0.441	*surrender*	0.453
suspicious	0.484	*failing*	0.531	*warms*	0.391	*beggar*	0.422
oust	0.484	*stressed*	0.531	*gesture*	0.387	*difficulties*	0.421
ultimatum	0.439	*disgusting*	0.484	*healing*	0.328	*perpetrator*	0.359
deleterious	0.438	*hallucination*	0.484	*tribulation*	0.328	*hindering*	0.359

Table 1: Example entries for four (of the eight) emotions in the NRC Affect Intensity Lexicon. For each emotion, the table shows every 100th and 101th entry, when ordered by decreasing emotion intensity.

Linguistic Inquiry and Word Count

- Approximately 2300 words across 73 lexical resources associated with different psychological tasks
  - Pennebaker, J. W., Booth, R. J., and Francis, M. E. (2007). *Linguistic Inquiry and Word Count: LIWC 2007*. Austin,TX.
- Link:
  - https://www.liwc.app/
- Actively maintained and updated (most recent version is from 2022)
- Not free!

RESULTS

Traditional LIWC Dimension	Your Text	Average for E-mail Language
I-words (I, me, my)	2.10	1.85
Positive Tone	2.40	2.20
Negative Tone	0.00	0.50
Social Words	8.71	6.07
Cognitive Processes	10.81	11.40
Allure	4.50	4.83
Moralization	0.00	0.07
Summary Variables		
Analytic	71.65	75.99
Authentic	80.33	36.72

Brysbaert Concreteness Lexicon

- Approximately 40,000 words labeled with continuous concreteness labels ranging from 1-5
  - Brysbaert, M., Warriner, A.B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods*, 46, 904-911.
- Link:
  - http://crr.ugent.be/archives/1330

Word	Bigram	Conc.M	Conc.SD
roadsweeper	0	4.85	0.37
traindriver	0	4.54	0.71
tush	0	4.45	1.01
hairdress	0	3.93	1.28
pharmaceutics	0	3.77	1.41
hoover	0	3.76	1.23
shopkeeping	0	3.18	1.19
pushiness	0	2.48	1.24
underdevelop	0	2.37	1.4
tirelessness	0	2.28	1.28
oldfashioned	0	2.26	1.02
wellmannered	0	2.25	1.14
dismissiveness	0	1.83	1
spitefulness	0	1.8	0.76
untruthfulness	0	1.73	0.92
dispiritedness	0	1.56	0.71
sled	0	5	0
plunger	0	4.96	0.2
human	0	4.93	0.26
waterbed	0	4.93	0.27
cymbal	0	4.92	0.28
ginger	0	4.92	0.27
bobsled	0	4.9	0.41
cardboard	0	4.9	0.41
olive	0	4.9	0.31
dogsled	0	4.89	0.32

Personality and Stance

- Two other popular forms of affective analysis:
  - Personality detection
  - Stance detection
- Personality detection focuses on recognizing and classifying predefined aspects of a user's personal character
  - Most work in NLP makes use of the "Big Five" **personality dimensions**
- Stance detection focuses on recognizing a user's opinion towards a specific topic
  - Friendly
  - Distant
  - Supportive
  - Unsupportive

Predicting and Visualizing Affective Scores

- **Potts Diagrams:** Mechanism for visualizing word sentiment
  - Sentiment class vs. normalized word likelihood
    - $P(w|c) = \frac{\text{count}(w,c)}{\sum_{w \in C} \text{count}(w,c)}$
- Characteristic patterns:
  - **"J" shape:** Strongly positive word
  - **Reverse "J" shape:** Strongly negative word
  - **"Hump" shape:** Weakly positive or negative word
- Patterns may also correspond to different types of word classes
  - Emphatic and attenuating adverbs

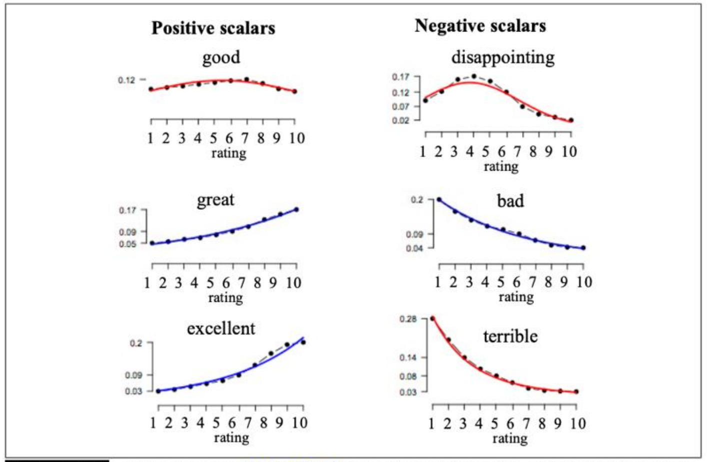


Figure 21.10 Potts diagrams (Potts, 2011) for positive and negative scalar adjectives, showing the J-shape and reverse J-shape for strongly positive and negative adjectives, and the hump-shape for more weakly polarized adjectives.

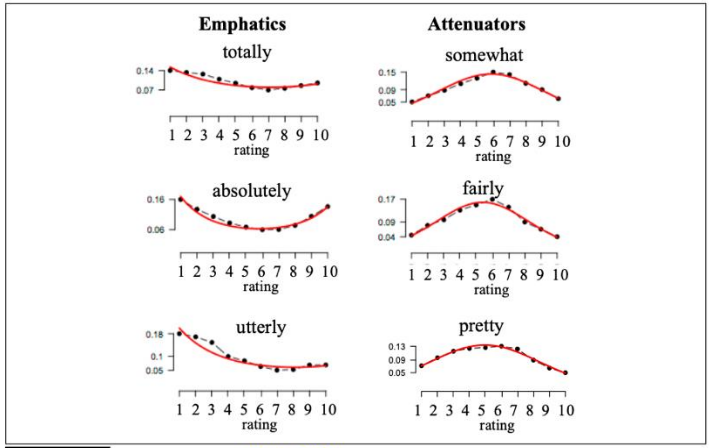


Figure 21.11 Potts diagrams (Potts, 2011) for emphatic and attenuating adverbs.

Log Odds Ratio with an Informative Dirichlet Prior

- Allows us to determine which words are closely associated with different classes
- Originally proposed for measuring partisan speech used by US politicians
- Generalizes to any other problem domain for which lexical trends are anticipated to be different between groups
- Key goal: Find words that are statistically overrepresented in one category of text compared to another

Start with a simple log odds ratio….

- **Probability of word *w* existing in a subset of words *i*:**
  - $P^i(w) = \frac{f_w^i}{n^i}$

Total number of words in *i*

- **Log odds ratio for word *w* in the subset of words *i* versus the subset of words *j*:**
  - $\mathrm{lor}(w) = \log \frac{P^i(w)}{1-P^i(w)} - \log \frac{P^j(w)}{1-P^j(w)} = \log \frac{f_w^i}{n^i - f_w^i} - \log \frac{f_w^j}{n^j - f_w^j}$

- Dirichlet intuition: Use a large background corpus to get a prior estimate of our expected frequency for each word *w*
  - To do so, add the counts from that corpus to our numerator and denominator

Prior-Modified Log Odds Ratio

- Modifying the previous equation with an informative Dirichlet prior:
  - $\delta_w^{(i-j)} = \log \frac{f_w^i + \alpha_w}{n^i + \alpha_0 - (f_w^i + \alpha_w)} - \log \frac{f_w^j + \alpha_w}{n^j + \alpha_0 - (f_w^j + \alpha_w)}$

Number of words in *i*

Count of *w* in corpus

Size of background corpus

Count of w in background corpus

Log Odds Ratio with Informative Dirichlet Prior

- Estimate of variance for the modified log odds ratio:
  - $\sigma^2\left(\hat{\delta}_w^{(i-j)}\right) \approx \frac{1}{f_w^i + \alpha_w} + \frac{1}{f_w^j + \alpha_w}$
  - Controls for the amount of variance in a word's frequency
- Final statistic for a word is then the z-score of its modified log odds ratio:
  - $\frac{\hat{\delta}_w^{(i-j)}}{\sqrt{\sigma^2\left(\hat{\delta}_w^{(i-j)}\right)}}$

This ultimately gives us a useful tool for analysis!

Words associated with one-star restaurant reviews

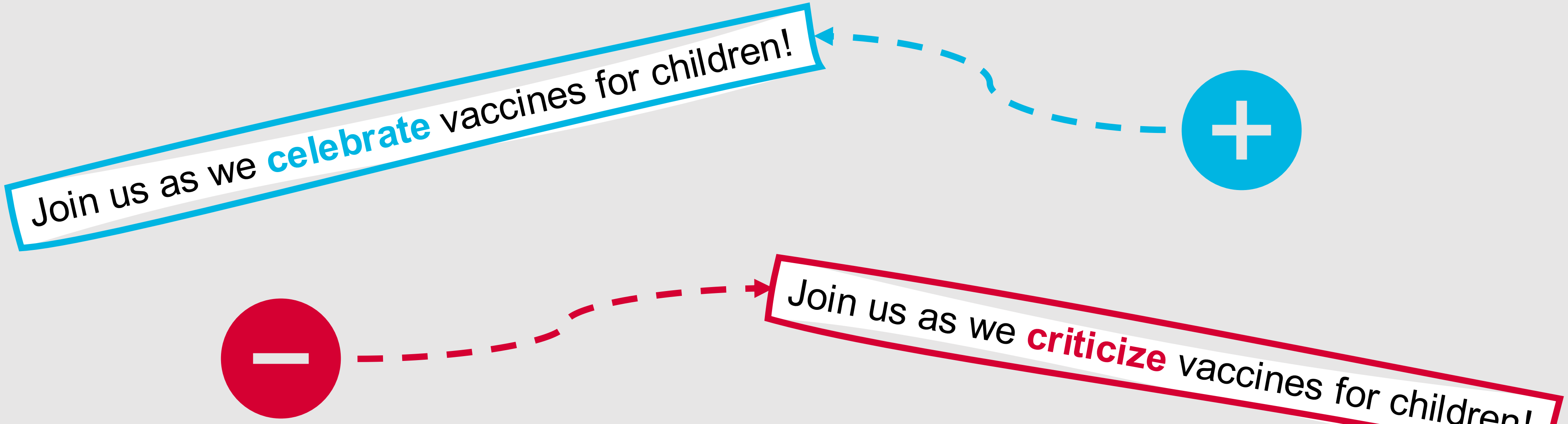
worst, rude, terrible, horrible, bad, awful, disgusting, bland, tasteless, gross, mediocre, overpriced, worse, poor

Words associated with five-star restaurant reviews

Great, best, love, delicious, amazing, favorite, perfect, excellent , awesome, friendly, fantastic, fresh, wonderful, incredible, sweet, yum

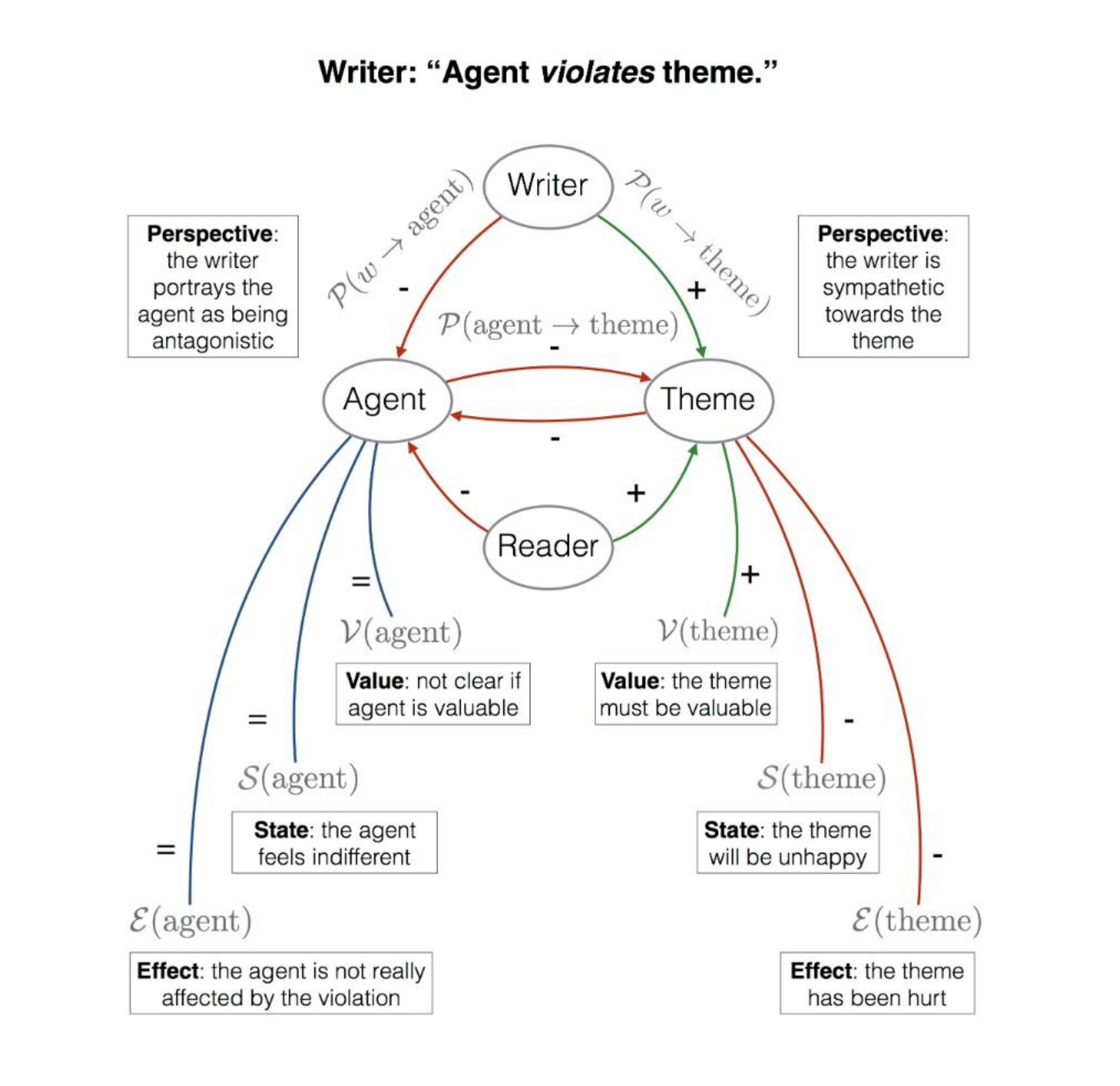
Connotation Frames

- We can also represent affective meaning using **connotation frames**
  - Indicate affective properties commonly associated with words, similarly to how verb frames indicate selectional preferences



Example Connotation Frame

- Relevant papers:
  - Hannah Rashkin, Sameer Singh, Yejin Choi. 2016. Connotation Frames: A Data-Driven Investigation. In Proceedings of ACL 2016.
    - https://aclanthology.org/P16-1030/
  - Maarten Sap, Marcella Cindy Prasettio, Ari Holtzman, Hannah Rashkin, & Yejin Choi. 2017. Connotation Frames of Power and Agency in Modern Films. In Proceedings of EMNLP 2017 Short Papers.
    - https://aclanthology.org/D17-1247/
- Relevant resource for measuring social dynamics between personas: https://github.com/maartensap/riveter-nlp
- Downloadable collection of connotation frames:
  - https://hrashkin.github.io/connframe.html

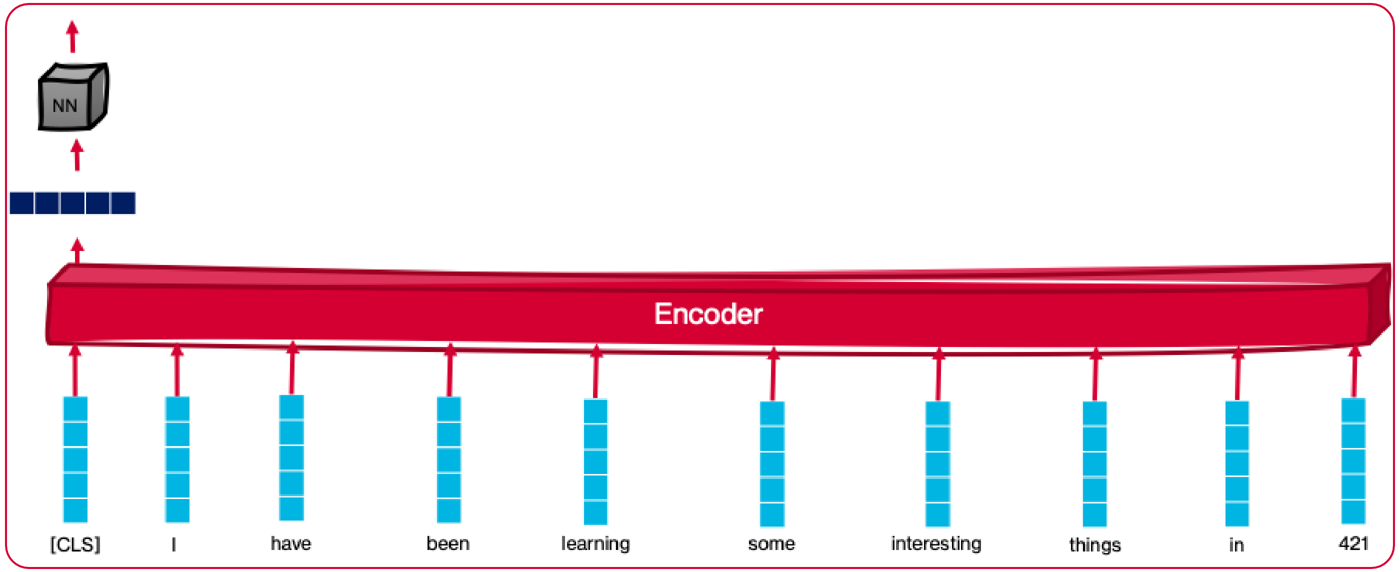


Stance Detection

- The task of determining sentiment with respect to a specific target (often a polarizing topic)
- Stance labels are generally some variation of **favor** and **against**
- Numerous datasets exist for this task:
  - **SemEval-2016 Task 6A Stance Dataset**
    - 4870 tweets manually annotated for stance with respect to: “Atheism,” “Climate Change is Real Concern,” “Feminist Movement,” “Hilary Clinton,” and “Legalization of Abortion”
  - **Multi-Perspective Consumer Health Query Data**
    - Relevant sentences from the top 50 links corresponding to common, polarizing or widely debated public health queries (e.g., “Does the MMR vaccine lead to autism in children?”)
  - **Ideological Online Debates**
    - Online debates on “Existence of God,” “Healthcare,” “Gun Right,” “Gay Rights,” and “Abortion and Creationism”

How can we build stance detection models?

- Predict favor and against (and optionally neutral) labels for each target *or* determine the relevant target as a preliminary step
- Feature-based approaches:
  - Text content
  - (If known) user-specific attributes
  - (If known) network-specific attributes
- Neural approaches:
  - Typically framed as a supervised instance-level classification task



Summary: Temporality and Affect

- **Named entity recognition** identifies the specific entities that participate in structured relationships or events
- **Relations** can be extracted using a variety of approaches
  - **Hearst patterns** are specialized rules for extracting relations
  - **Semi-supervised** learning or **distant supervision** can be used to extract relations without using a large labeled training set
  - **Open information extraction** uses unsupervised methods to extract relations
- **Temporal expressions** allow us to understand how events are situated within time
- We can represent **temporal logic** using the first-order logic framework and incorporating **interval algebra**
- Approaches for **temporal analysis** focus on extracting temporal expressions, normalizing those expressions, and using the extracted and normalized temporal information to place events in a structured order
- Emotion can be represented using fixed **atomic units** or **dimensions** in a continuous space
- Words can be assigned weights in an **affective lexicon** based on frequency measures and ratio metrics like **log odds ratio with an informative Dirichlet prior**
- **Connotation frames** express richer affective relationships, similar to those seen with semantic frames
- **Stance detection** allows us to predict sentiment with respect to a specific target