NLP Tasks 2

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TA: Omkar Kulkarni (he)

https://laramartin.net/NLP-class/

Slides modified from Dr. Frank Ferraro & Dr. Jason Eisner

Learning Objectives

Distinguish between classification and regression, supervised and unsupervised learning

Formalize NLP Tasks at a high-level:

- What are the input/output for a particular task?
- What might the features be?
- What types of applications could the task be used for?

Enumerate different input scopes of tasks when thought of as classification

High-Level View of the Course

Part 1: Intro to NLP terms & ML concepts

Tasks	What you are trying to solve
Models & Evaluation	What you are making and how you know it's doing well
Vector Embeddings	A way of encoding features

High-Level View of the Course

Part 2: Evolution of the language model

N-Gram Language Models → Logistic Regression → Neural Language Models → Recurrent NNs → Seq2Seq Models → Transformers → Masked LMs → Large Language Models (Few shot)

High-Level View of the Course

Part 3: Language Model Extensions

- Alignment
- Small “Large” Language Models
- RAG

High-Level View of the Course

Part 4: In-depth dives into certain applications

- Automatic Speech Recognition
- Machine Translation
- Dialog Systems

Review: Helpful ML Terminology

Model:

Weights/parameters (θ):

Objective function:

Evaluation function:

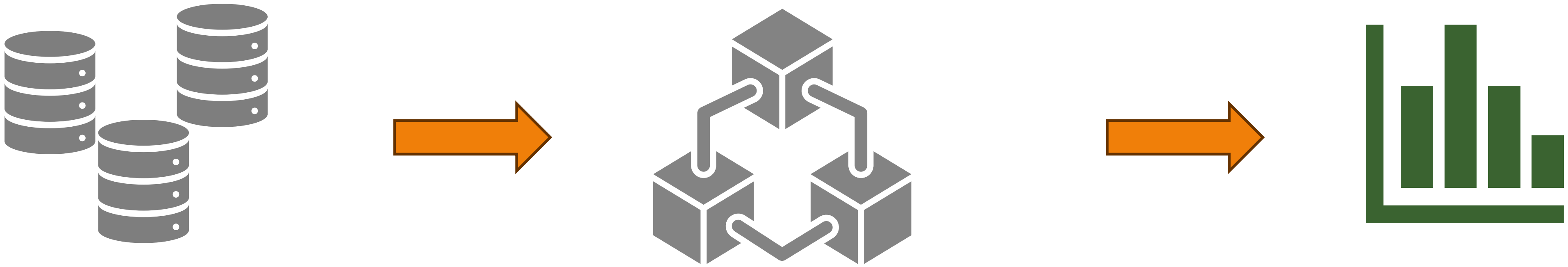
Review: Helpful ML Terminology

Training / Learning:

Inference / Prediction / Decoding / Classification:

Features:

How do we learn models?

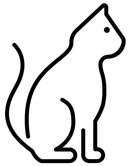


Take past experiences
(lots of data; corpus)

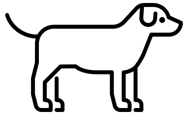
Find patterns
(the ML algorithm)

Use on new experiences
(save & test the model)

How do we learn models?



cat



dog

hamster

[position of lines]
[loops and dots]
[any other information relevant to our problem]

P(hamster|[line in this position],…)

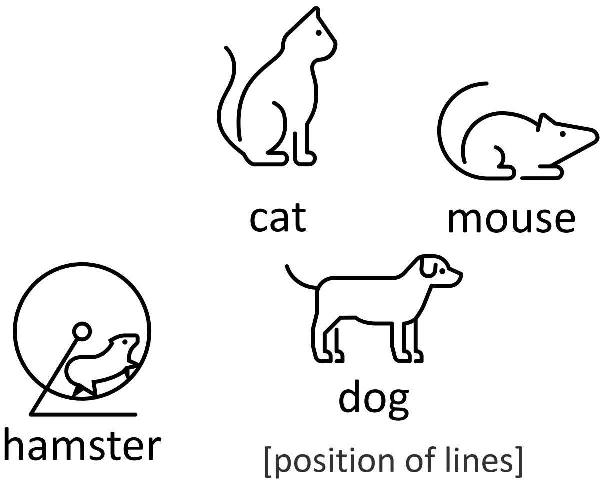
P(dog|[line in this other position],…)

Have data with features extracted (and possibly labels)

Learn associations between features and labels

Dividing up data for Training

Why would we do this?



[position of lines]
[loops and dots]
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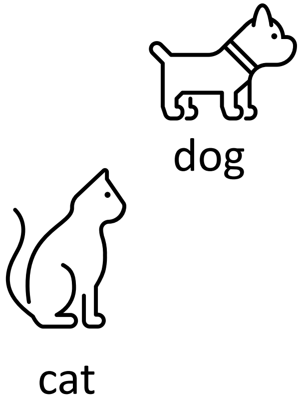
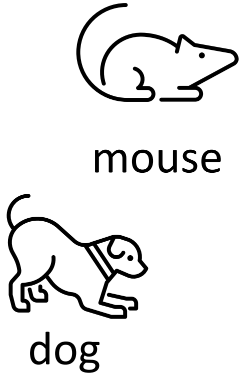




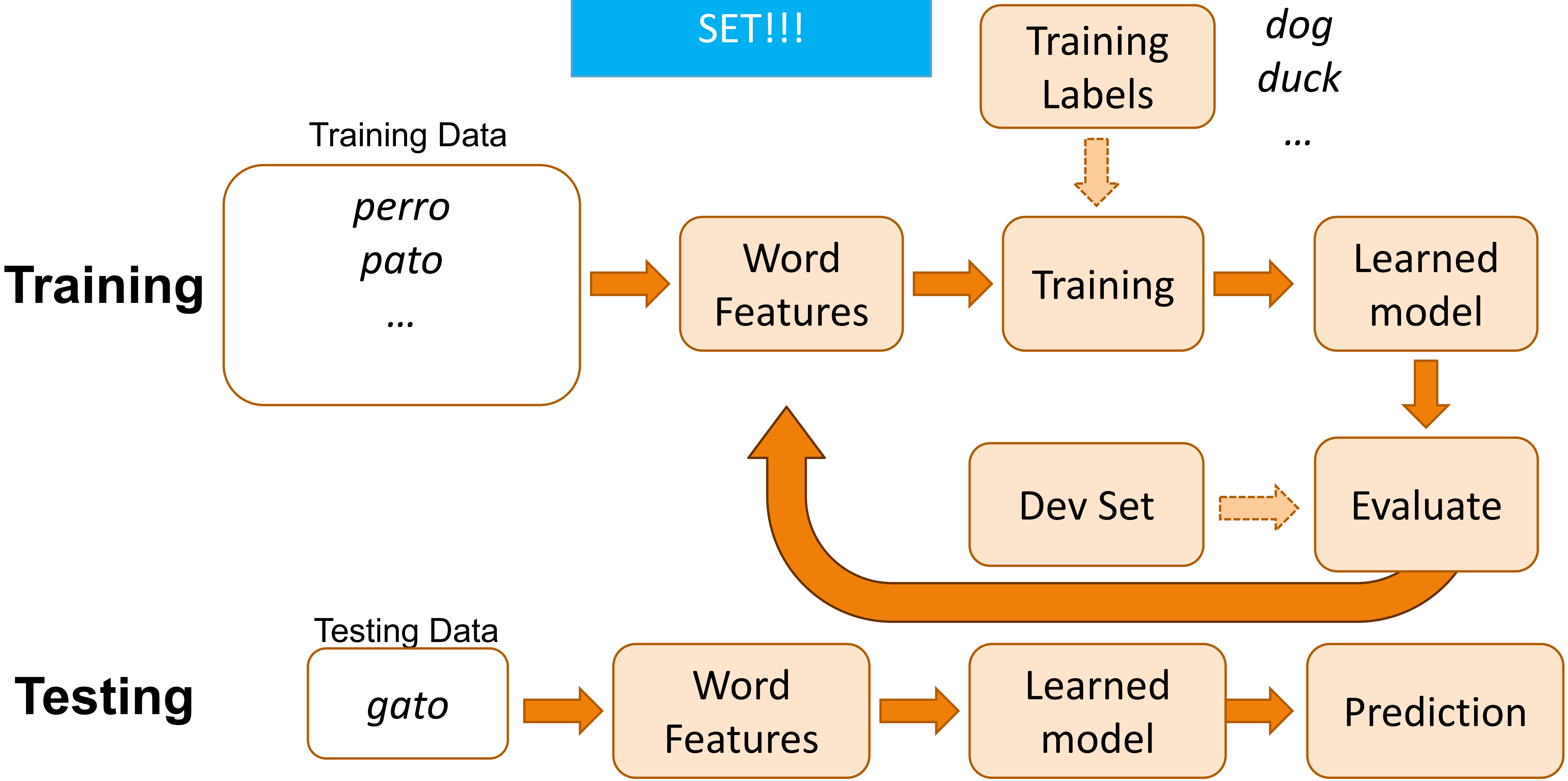
Training
~80%

Validation/Development
~10%

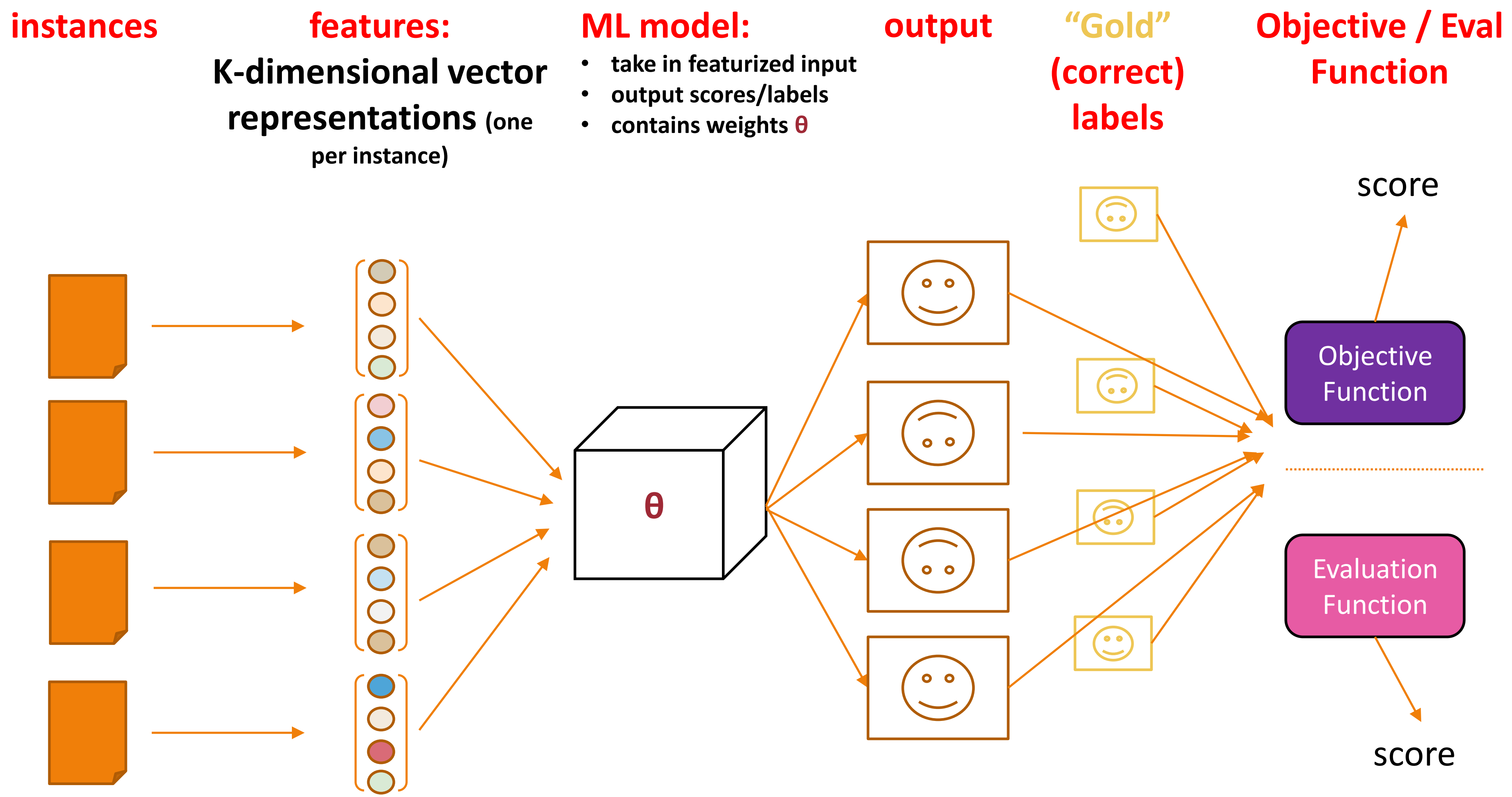
Testing
~10%

Steps

DO NOT ITERATE ON THE TESTING SET!!!



Review: ML/NLP Framework for Learning & Prediction



The Machine Learning Framework

$$y = f(\mathbf{x})$$

output

prediction function

feature(s) of input

Training: given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set

Testing: apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Slide credit: Svetlana Lazebnik

Types of models

CLASSIFICATION

Model outputs comes from a finite set of values

Discrete result

Examples:

- What type of animal is this a picture of?
- Predicting the weather (sunny, cloudy, or rainy?)
- Ranking: Is this result *better* than this result?

REGRESSION

Model outputs are continuous values

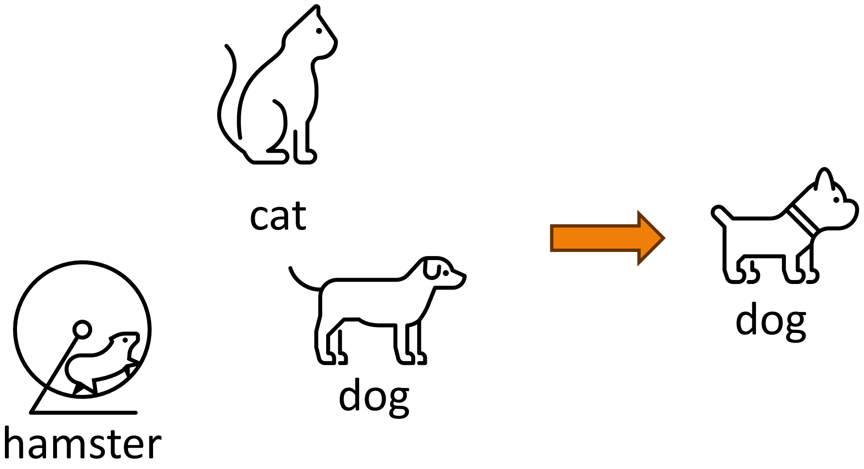
Continuous result

Examples:

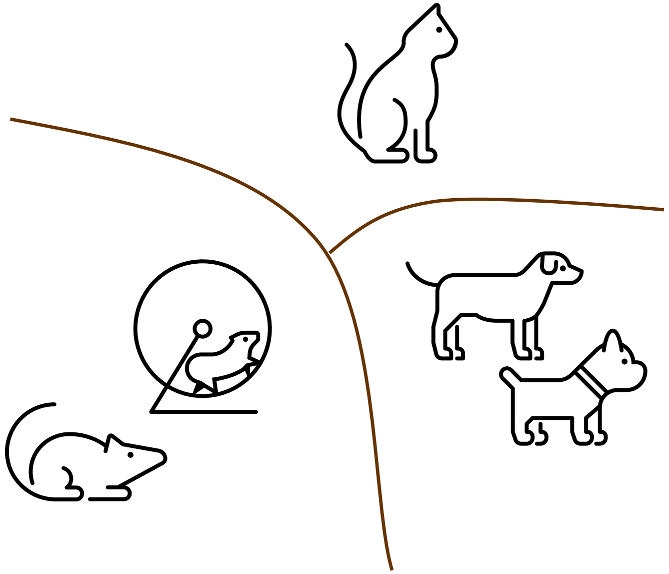
- How far will I move if I drive my motors at this speed for 1 second?
- Predicting the weather (temperature)
- Ranking: *how good* is this result?

Types of Learning

SUPERVISED LEARNING



UNSUPERVISED LEARNING



Types of Learning

SUPERVISED LEARNING

Data has feedback (labels)

Data consists of input-output pairs

Learn mapping from input to output

Examples:

- Dataset classification
- How likely is it that this person will get into a car accident?

UNSUPERVISED LEARNING

No explicit feedback in data

Learn patterns directly from data

Examples:

- Clustering
- Do these people fall under multiple groups?

What are some other examples of these?

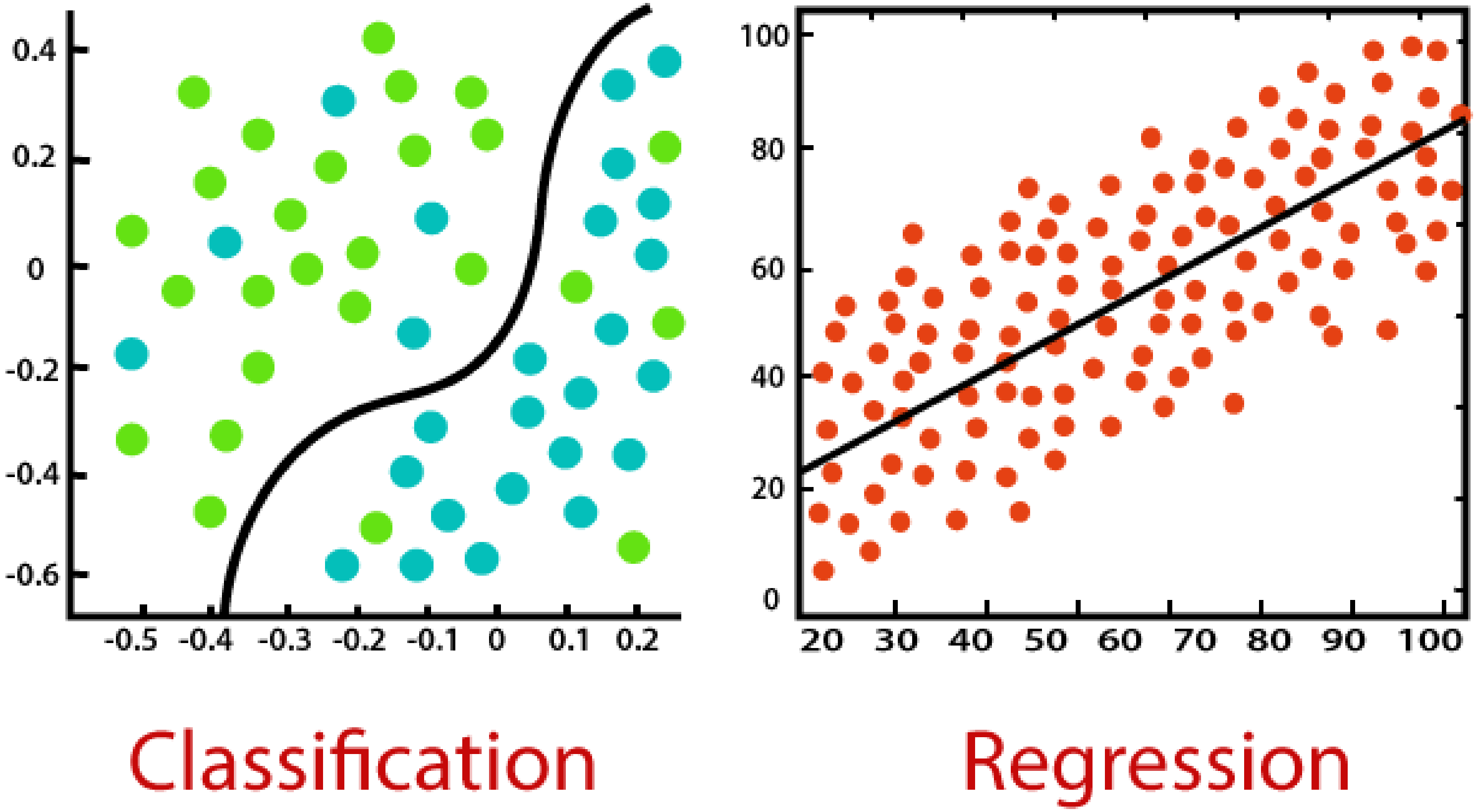
SUPERVISED LEARNING

- Machine translation
- Object segmentation (vision)
- Document classification

UNSUPERVISED LEARNING

- Clustering
- Language modeling

Types of models



https://medium.com/unpackai/classification-regression-in-machine-learning-7cf3b13b0b09

What are some other examples of these?

CLASSIFICATION

Tone tagging

Sentiment classification

Named entity recognition

REGRESSION

Quantity/scale of how much it sounds like a specific author

Numerical sentiment value

Political "score" from document

Likelihoods

Predicted Goodreads score

Types of Algorithms

	Supervised Learning	Unsupervised Learning
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

Text Annotation Tasks ("Classification" Tasks)

1. Classify the entire document ("text categorization")
2. Classify word tokens individually
3. Classify word tokens in a sequence
4. Identify phrases ("chunking")
5. Syntactic annotation (parsing)
6. Semantic annotation

Slide courtesy Jason Eisner, with mild edits

Different ways of categorizing tasks

By purpose:

- Capabilities: test key abilities (linguistic, social, cultural, etc.) of language understanding
  e.g., part-of-speech tagging, parsing, commonsense reasoning
- Application: a use case with potential products in mind
  e.g., machine translation, question answering
- NLP + X: new dimensions of capabilities and applications
  e.g., multilingual, multimodal

By model:

- Classification: output is a categorical variable
- Structured prediction: output is a chain, tree, or graph
- Generation: output is free-form text

Slide courtesy He He with mild edits

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Review: Questions to consider...

- **What are the input/output for this task?**
- What might the features be?
- What types of applications could the task be used for?

Input

Electronic alerts have been used to assist the authorities in moments of chaos and potential danger: after the Boston bombing in 2013, when the Boston suspects were still at large, and last month in Los Angeles, during an active shooter scare at the airport.

Output

TECH

NOT TECH

Review: Document Classification Features

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TECH

NOT TECH

feature extraction

feature $f_i(x)$	value
alerts	1
assist	1
bombing	1
Boston	2
…	
sniffle	0
…	

- What are the input/output for this task?
- **What might the features be?**
- What types of applications could the task be used for?

Review: Document Classification Applications

Assigning subject categories, topics, or genres

Spam detection

Authorship identification

Language Identification

Sentiment analysis

…

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Review: Token Classification

Word pronunciation

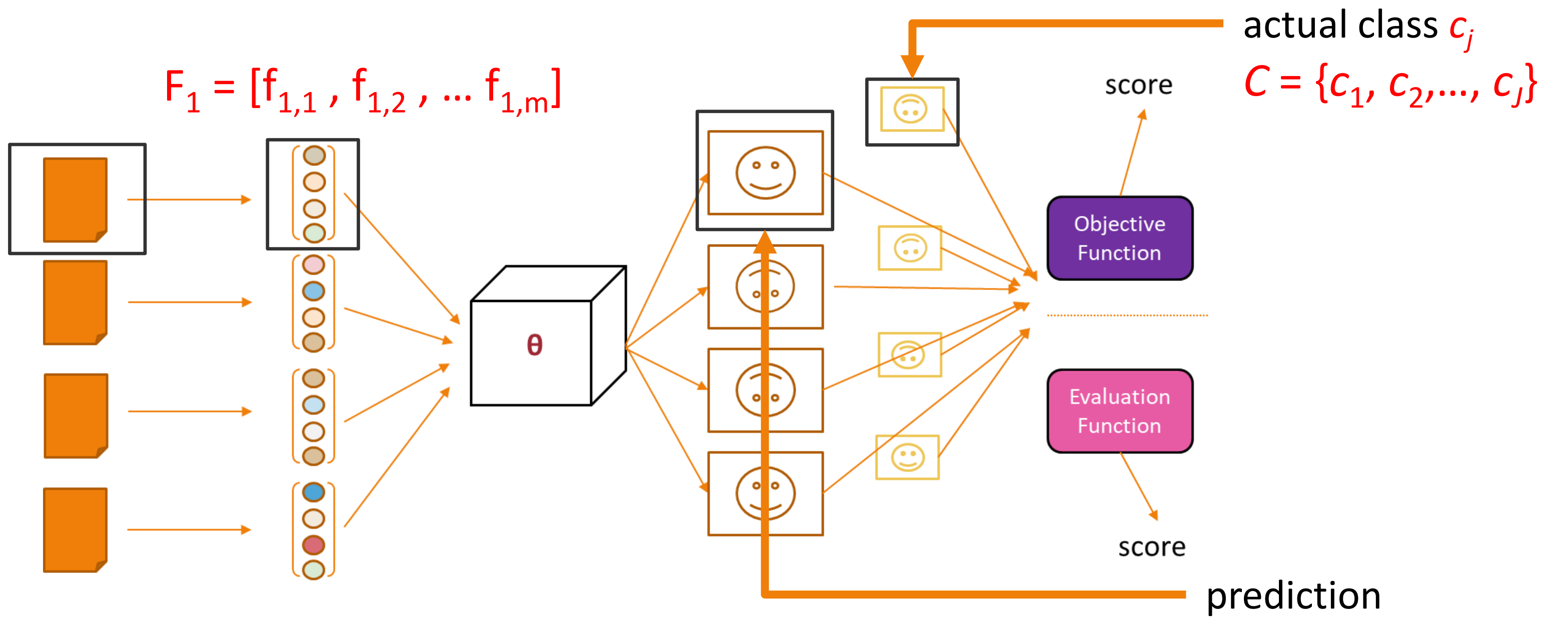
Word sense disambiguation (WSD) within or across languages

Accent restoration

…

Applications

features F_1 extracted from word w_1 and its surrounding words (context)



Text Annotation Tasks (“Classification” Tasks)

1. Classify the entire document (“text categorization”)
2. Classify word tokens individually
3. Classify word tokens in a sequence (i.e., order matters)
4. Identify phrases (“chunking”)
5. Syntactic annotation (parsing)
6. Semantic annotation
7. Text generation

Slide courtesy Jason Eisner, with mild edits

Example: Part of Speech Tagging

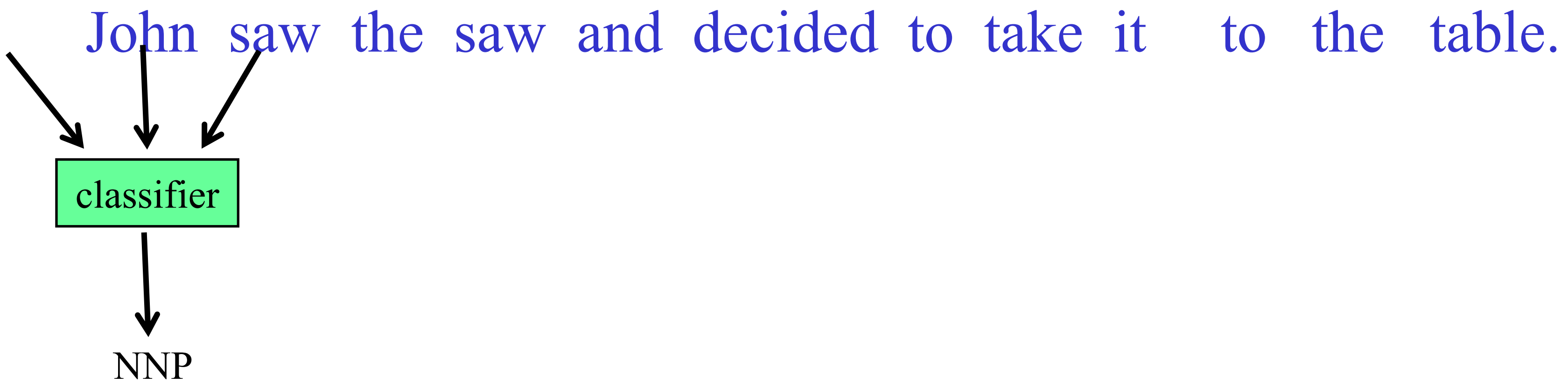
We could treat tagging as a token classification problem

- Tag each word independently given features of context
- And features of the word's spelling (suffixes, capitalization)

Slide courtesy Jason Eisner, with mild edits

Sequence Labeling as Classification

Classify each token independently but use as input features, information about the surrounding tokens (sliding window).



Slide courtesy Ray Mooney, with mild edits

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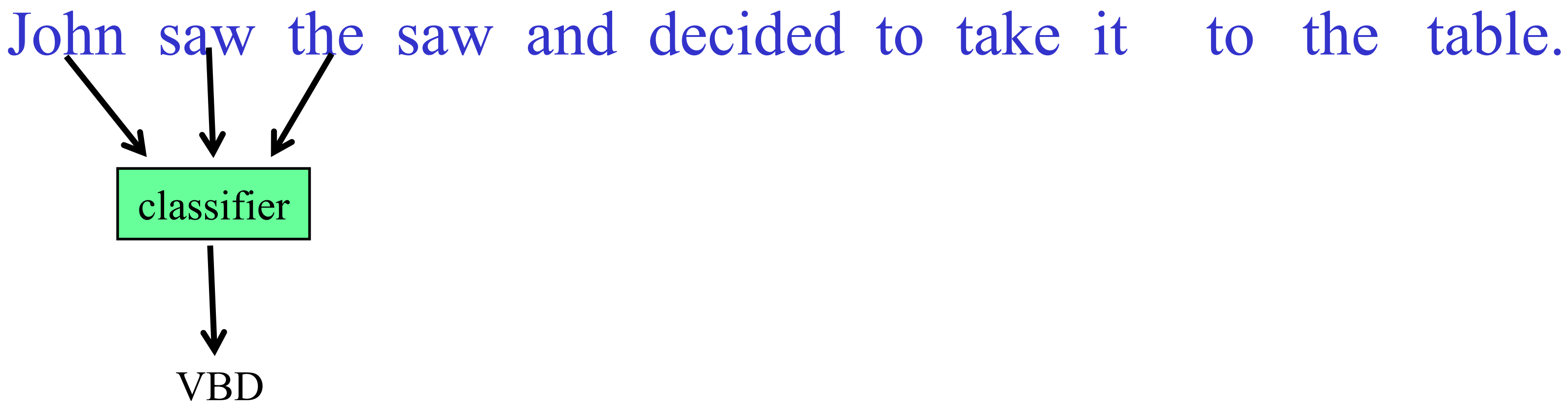

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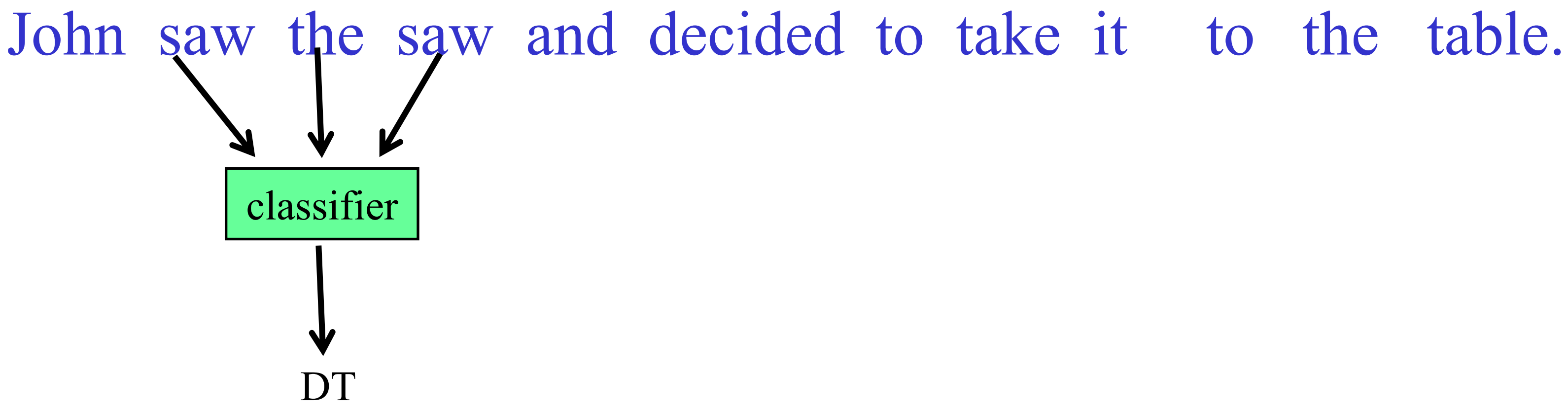

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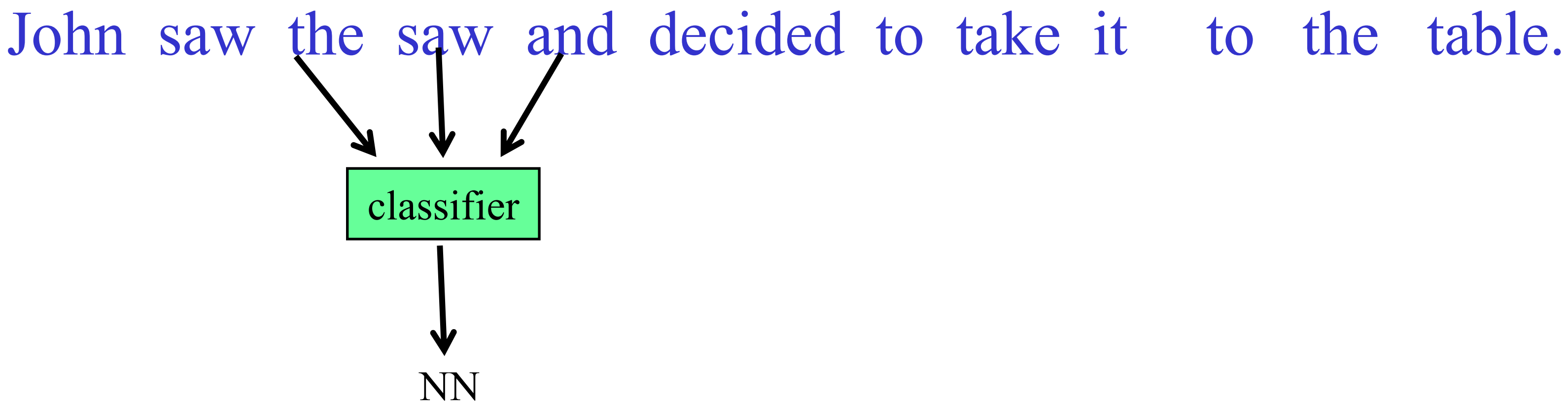

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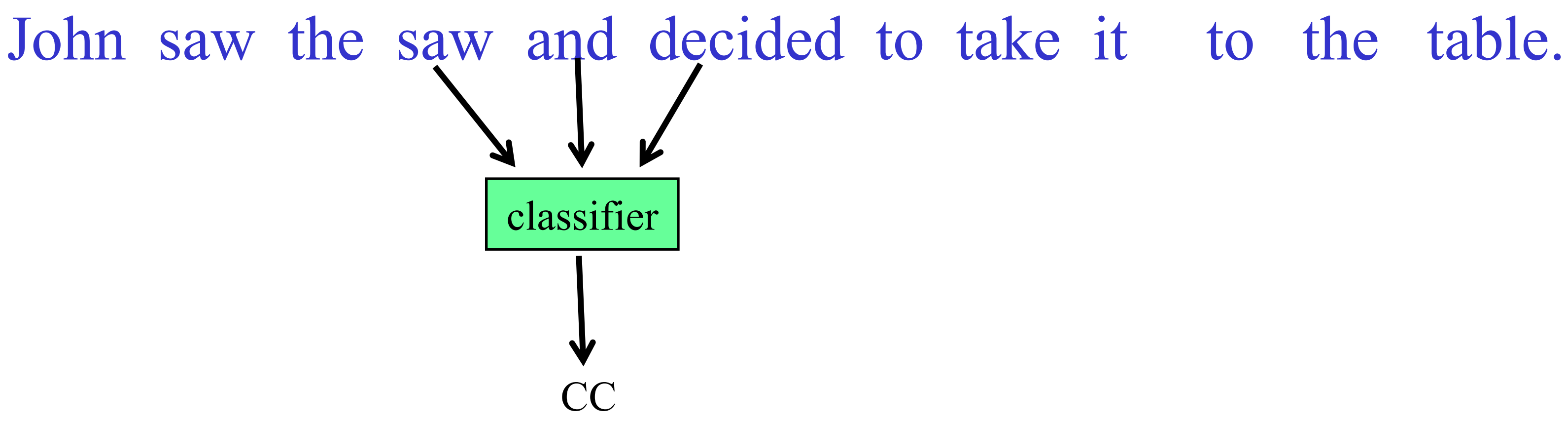

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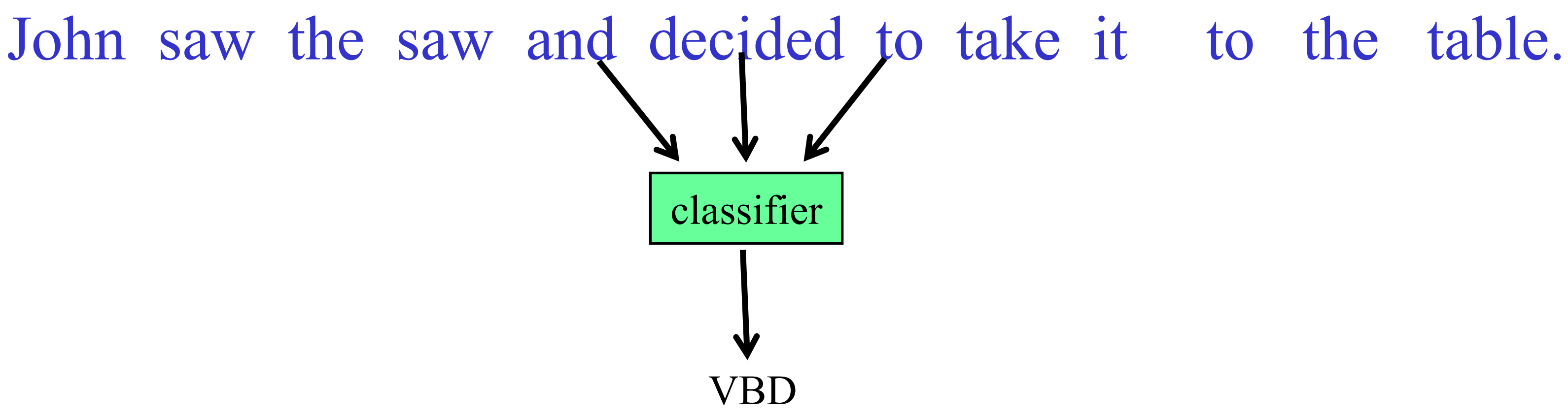

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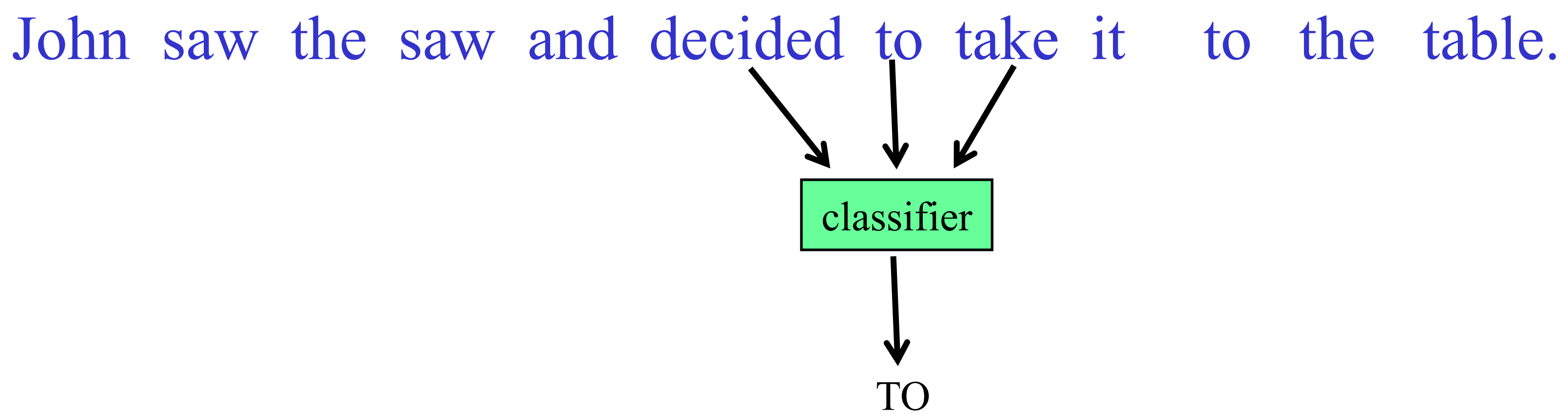

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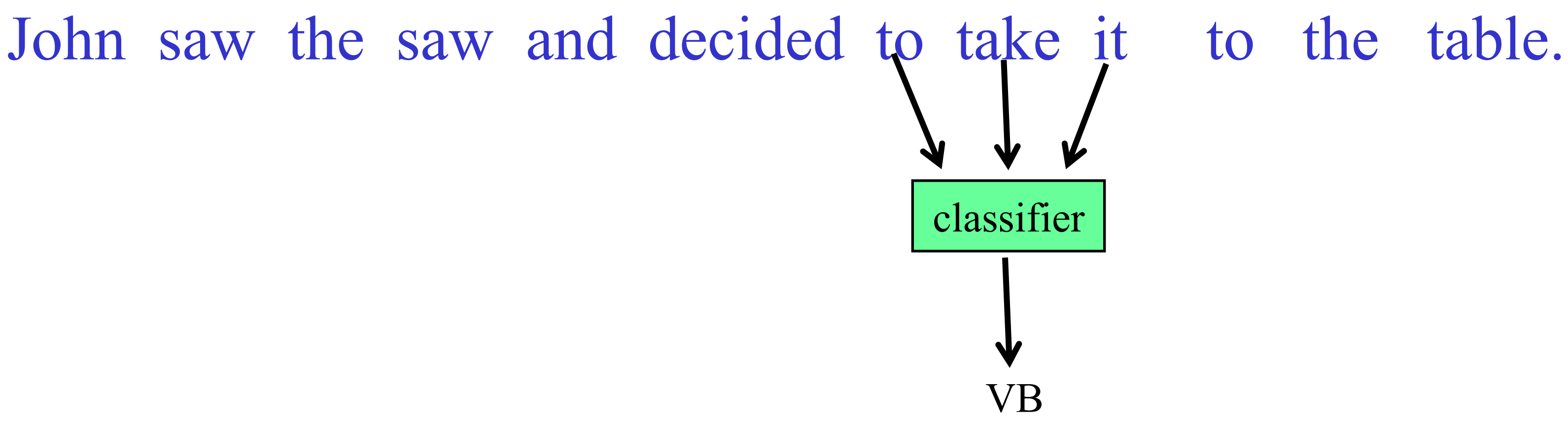

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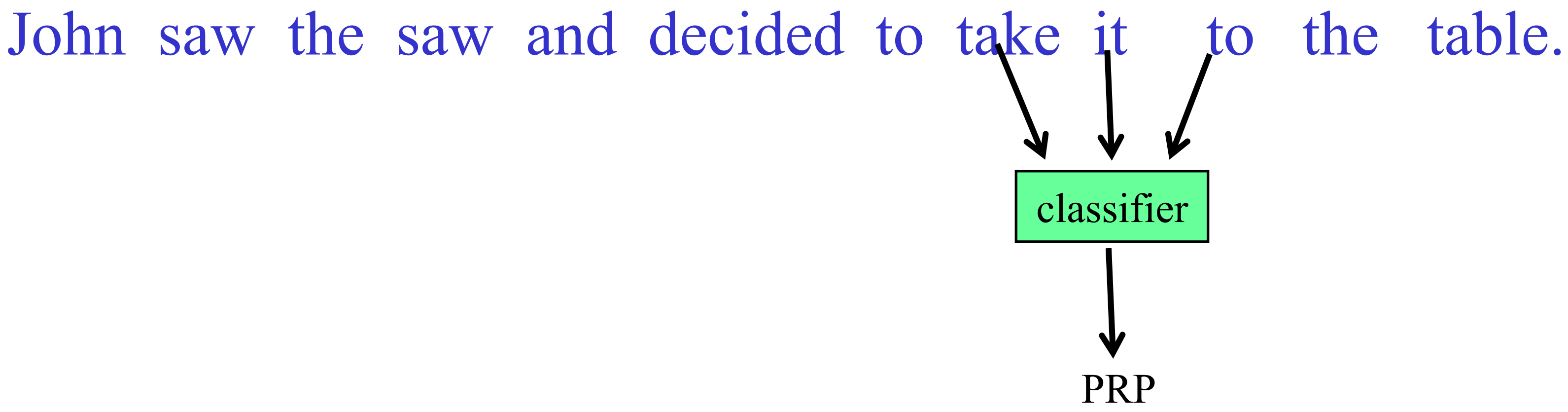

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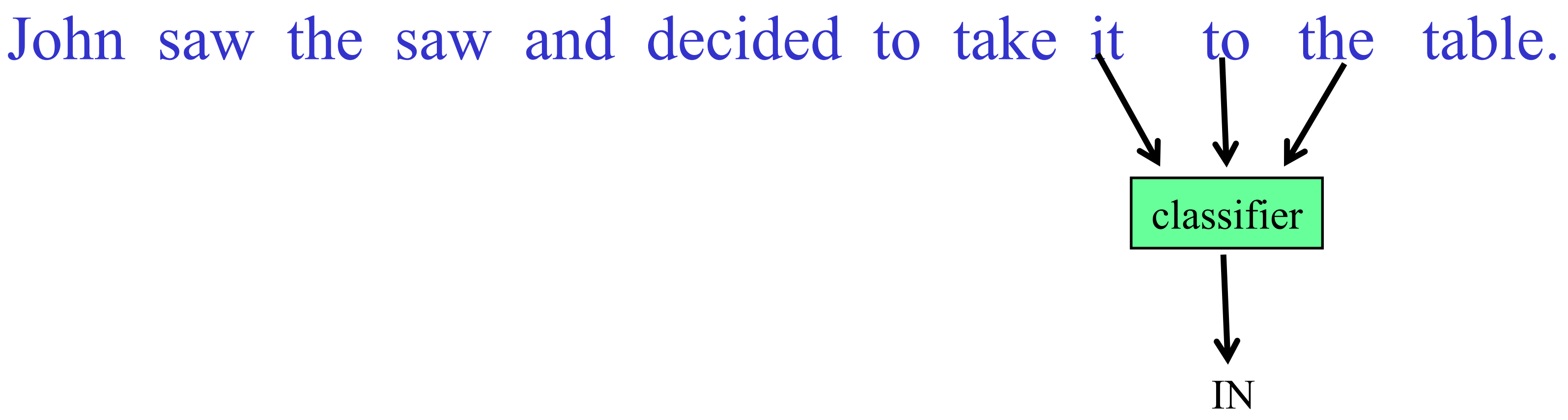

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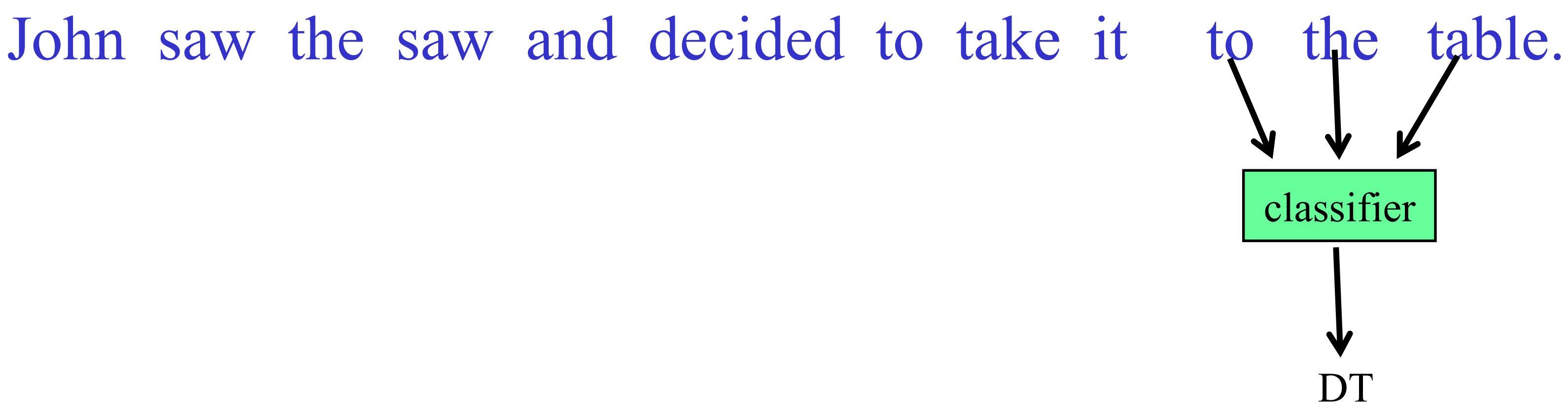
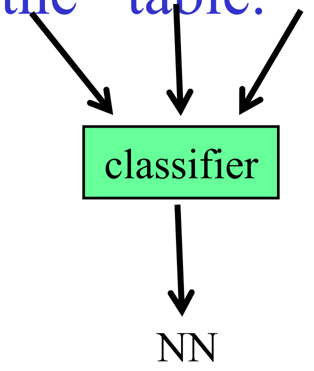


Slide courtesy Ray Mooney, with mild edits

Sequence Labeling as Classification

Classify each token independently but use as input features, information about the surrounding tokens (sliding window).

John saw the saw and decided to take it to the table.



What are the input/output?
What are the features?
What types of applications?

Slide courtesy Ray Mooney, with mild edits

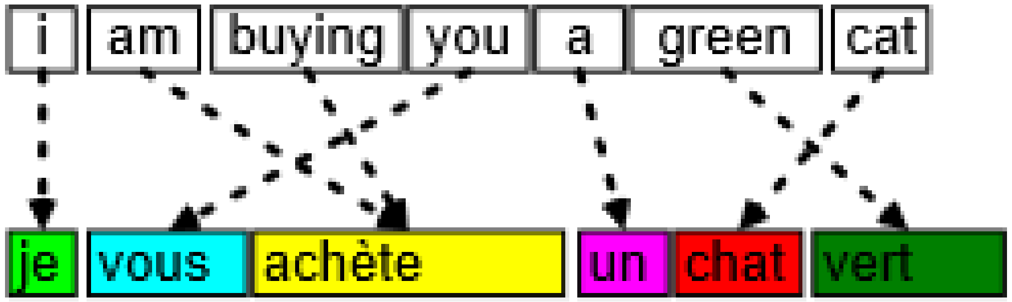
Token Classification in a Sequence Input/Output

Token Classification in a Sequence Applications

Part of speech tagging

Word alignment

Machine Translation: Word Alignment



What kinds of features might we want to consider here?

https://towardsdatascience.com/machine-translation-a-short-overview-91343ff39c9f

Token Classification in a Sequence

Other examples?

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Slide courtesy Jason Eisner, with mild edits

Example: Finding Named Entities

Named entity recognition (NER)

Identify proper names in texts, and classification into a set of predefined categories of interest

- Person names
- Organizations (companies, government organisations, committees, etc.)
- Locations (cities, countries, rivers, etc.)
- Date and time expressions
- Measures (percent, money, weight, etc.),
- email addresses, web addresses, street addresses, etc.
- Domain-specific: names of drugs, medical conditions,
- names of ships, bibliographic references etc.

Cunningham and Bontcheva (2003, RANLP Tutorial)

NE Types

Type	Tag	Sample Categories
People	PER	Individuals, fictional characters, small groups
Organization	ORG	Companies, agencies, political parties, religious groups, sports teams
Location	LOC	Physical extents, mountains, lakes, seas
Geo-Political Entity	GPE	Countries, states, provinces, counties
Facility	FAC	Bridges, buildings, airports
Vehicles	VEH	Planes, trains, and automobiles

Type	Example
People	*Turing* is often considered to be the father of modern computer science.
Organization	The *IPCC* said it is likely that future tropical cyclones will become more intense.
Location	The *Mt. Sanitas* loop hike begins at the base of *Sunshine Canyon*.
Geo-Political Entity	*Palo Alto* is looking at raising the fees for parking in the University Avenue district.
Facility	Drivers were advised to consider either the *Tappan Zee Bridge* or the *Lincoln Tunnel*.
Vehicles	The updated *Mini Cooper* retains its charm and agility.

Slide courtesy Jim Martin

Named Entity Recognition

CHICAGO (AP) — 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 AMR, immediately matched the move, spokesman Tim Wagner said. United, a unit of UAL, said the increase took effect Thursday night and applies to most routes where it competes against discount carriers, such as Chicago to Dallas and Atlanta and Denver to San Francisco, Los Angeles and New York.

What are the input/output?
What are the features?
What types of applications?

Slide courtesy Jim Martin

Chunking Input/Output

Chunking Applications

Named entity recognition

Information extraction

Identifying idioms

…

Example: Information Extraction

As a task: **Filling slots in a database from sub-segments of text.**

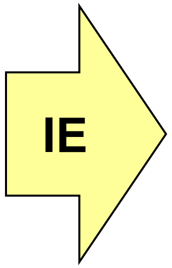
October 14, 2002, 4:00 a.m. PT

For years, Microsoft Corporation CEO Bill Gates railed against the economic philosophy of open-source software with Orwellian fervor, denouncing its communal licensing as a "cancer" that stifled technological innovation.

Today, Microsoft claims to "love" the open-source concept, by which software code is made public to encourage improvement and development by outside programmers. Gates himself says Microsoft will gladly disclose its crown jewels--the coveted code behind the Windows operating system--to select customers.

"We can be open source. We love the concept of shared source," said Bill Veghte, a Microsoft VP. "That's a super-important shift for us in terms of code access.“

Richard Stallman, founder of the Free Software Foundation, countered saying…



NAME	TITLE	ORGANIZATION
Bill Gates	CEO	Microsoft
Bill Veghte	VP	Microsoft
Richard Stallman	founder	Free Soft..

Slide from Chris Brew, adapted from slide by William Cohen

Example *applications* for IE

Classified ads

Restaurant reviews

Bibliographic citations

Appointment emails

Legal opinions

Papers describing clinical medical studies

Task vs application?

Slide courtesy Jason Eisner, with mild edits

Chunking

Named entity recognition

Information extraction

Identifying idioms

…

Other examples?

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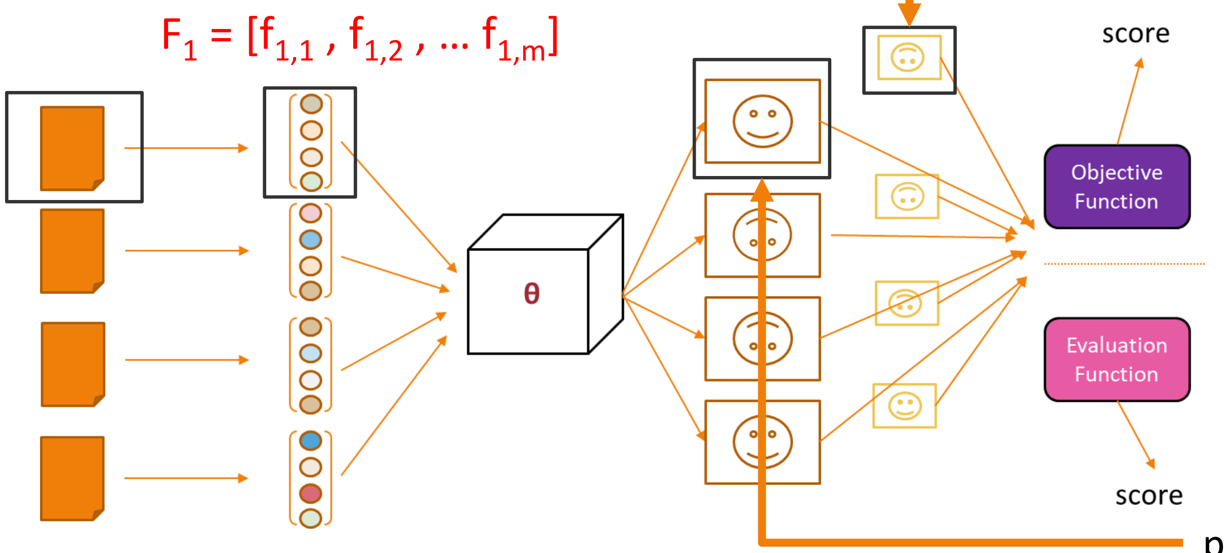
Syntax Parsing

features F_1 extracted from phrase/sentence s_1



actual parsed sentence p_1

predicted parsed sentence $\hat{p}_1$

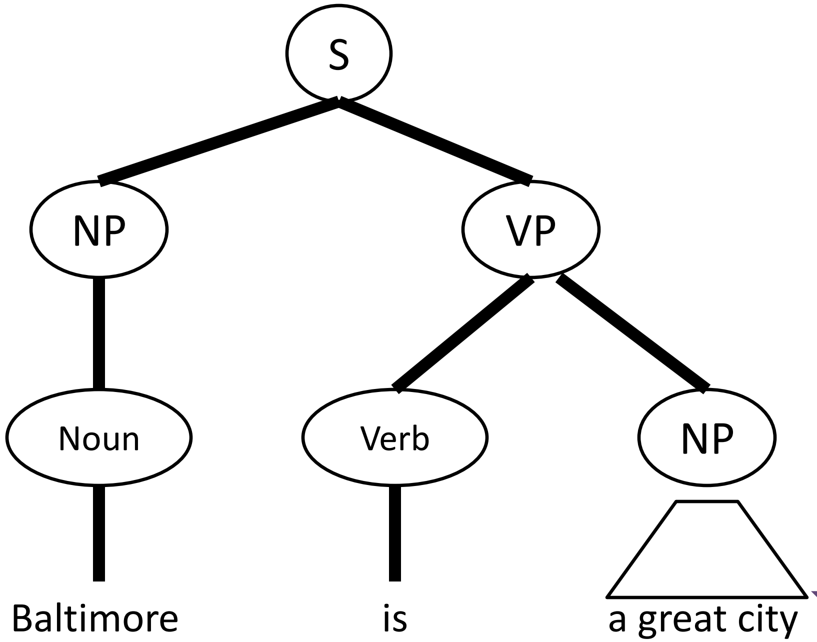
Context Free Grammar

S → NP VP	PP → P NP
NP → Det Noun	AdjP → Adj Noun
NP → Noun	VP → V NP
NP → Det AdjP	Noun → Baltimore
NP → NP PP	…

Set of rewrite rules, comprised of terminals and non-terminals

Generate from a Context Free Grammar

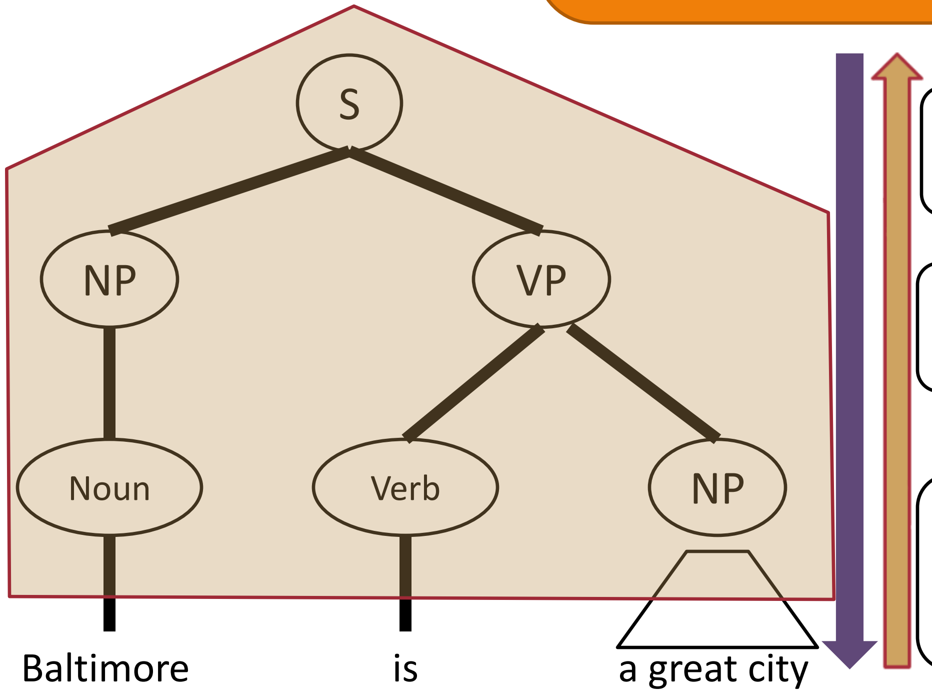
S → NP VP	PP → P NP
NP → Det Noun	AdjP → Adj Noun
NP → Noun	VP → V NP
NP → Det AdjP	Noun → Baltimore
NP → NP PP	…



Baltimore is a great city

Assign Structure (Parse) with a Context Free Grammar

S → NP VP	PP → P NP
NP → Det Noun	AdjP → Adj Noun
NP → Noun	VP → V NP
NP → Det AdjP	Noun → Baltimore
NP → NP PP	…



Baltimore is a great city

[$_{S}$ [$_{NP}$ [$_{Noun}$ Baltimore]] [$_{VP}$ [$_{Verb}$ is] [$_{NP}$ a great city]]]

bracket notation

(S (NP (Noun Baltimore))
(VP (V is)
(NP a great city)))

S-expression

Why is it useful?

https://www.housebeautiful.com/uk/garden/g45582875/garden-path-ideas/

Garden Path Sentences

The old man the boat .

https://www.housebeautiful.com/uk/garden/g45582875/garden-path-ideas/

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Garden Path Sentences

The rat the cat the dog chased killed ate the malt.


https://www.housebeautiful.com/uk/garden/g45582875/garden-path-ideas/

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The rat *that* the cat the dog chased killed ate the malt.

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Garden Path Sentences

https://www.housebeautiful.com/uk/garden/g45582875/garden-path-ideas/

[The rat [the cat [the dog chased] killed] ate the malt].

Language can have recursive patterns

Syntactic parsing can help identify those

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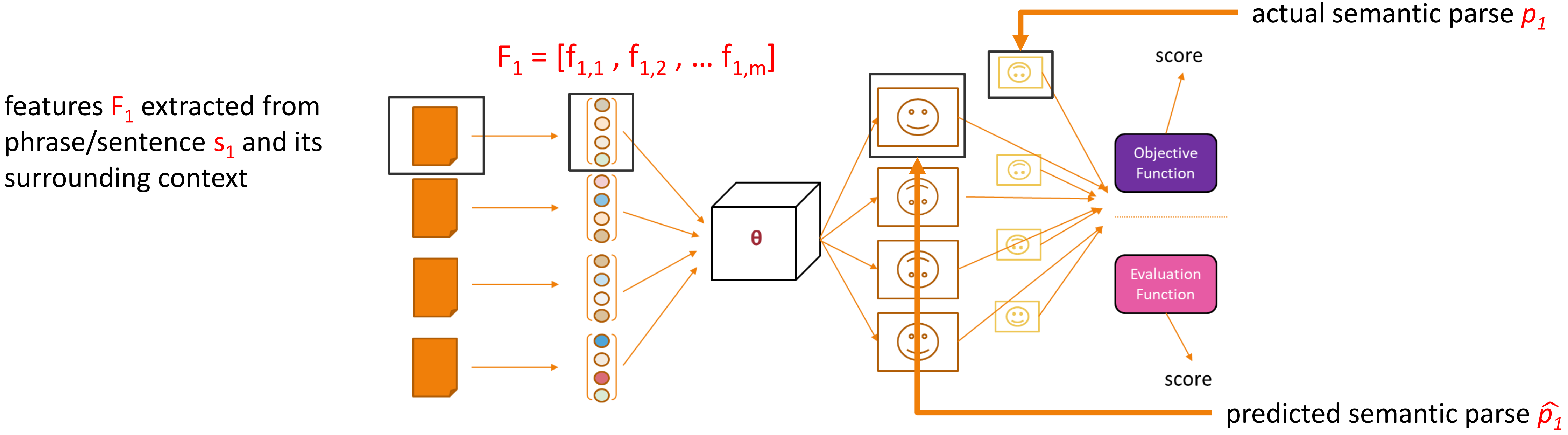
Semantic Parsing

Task: Semantic role labeling (SRL)

What is a semantic parse?



Semantic Role Labeling (SRL)

For each predicate (e.g., verb)

1. find its arguments (e.g., NPs)
2. determine their **semantic roles**

John drove Mary from Austin to Dallas in his Toyota Prius.

The hammer broke the window.

- agent: Actor of an action
- patient: Entity affected by the action
- source: Origin of the affected entity
- destination: Destination of the affected entity
- instrument: Tool used in performing action.
- beneficiary: Entity for whom action is performed

Slide thanks to Ray Mooney (modified)

Other Current Semantic Annotation Tasks (similar to SRL)

PropBank – coarse-grained roles of verbs

NomBank – similar, but for nouns

FrameNet – fine-grained roles of any word

TimeBank – temporal expressions

Slide courtesy Jason Eisner, with mild edits

What type of applications might this have?

FrameNet Example

REVENGE FRAME

Avenger
Offender (unexpressed in this sentence)
Injury
Injured Party (unexpressed in this sentence)
Punishment

We avenged the insult by setting fire to his village.

a word/phrase that triggers the REVENGE frame

Slide thanks to CJ Fillmore (modified)

Text Annotation Tasks ("Classification" Tasks)

1. Classify the entire document ("text categorization")
2. Classify word tokens individually
3. Classify word tokens in a sequence
4. Identify phrases ("chunking")
5. Syntactic annotation (syntax parsing)
6. Semantic annotation
7. Text generation

Slide courtesy Jason Eisner, with mild edits

Generation as a Classification Problem

Treating the word we want to generate as a label

What are the input/output?
What are the features?
What types of applications?

Text Generation Input/Output

Text Generation Applications