NPFL123 Dialogue Systems

4. Language Understanding vol. 1 (non-neural)

https://ufal.cz/npfl123

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Natural Language Understanding

- **words → meaning**
  - whatever "meaning" is – can be different tasks
  - typically structured, explicit representation
- alternative names/close tasks:
  - **spoken language understanding**
  - **semantic decoding/parsing**
- integral part of dialogue systems, also explored elsewhere
  - stand-alone semantic parsers
  - other applications:
    - human-robot interaction
    - question answering
    - machine translation (not so much nowadays)

NLU Challenges

- non-grammaticality
  find something cheap for kids should be allowed
- disfluencies
  - hesitations – pauses, fillers, repetitions
  - fragments
  - self-repairs (~6%!)

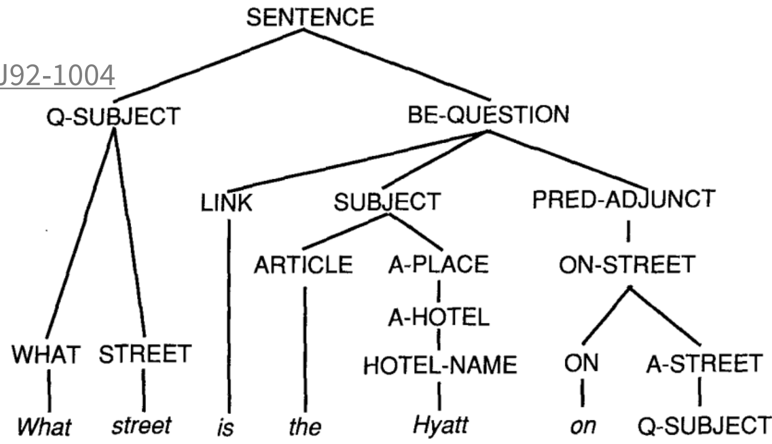
  uhm I want something in the west the west part of town
  uhm find something uhm something cheap no I mean moderate
  uhm I'm looking for a cheap
- ASR errors
  I'm looking for a for a chip Chinese rest or rant
- synonymy
  Chinese city centre
  uhm I've been wondering if you could find me a restaurant that has Chinese food close to the city centre please
- out-of-domain utterances
  oh yeah I've heard about that place my son was there last month

Semantic representations

- syntax/semantic **trees**
  - typical for standalone semantic parsing
  - different variations
- **frames**
  - technically also trees, but not directly connected to words
  - (mostly older) DSs, some standalone parsers
- **graphs** (AMR)
  - more of a toy task, but popular
- **dialogue acts** = intent + slots & values
  - flat – no hierarchy
  - most DSs nowadays

inform(date=Friday, stay="2 nights")

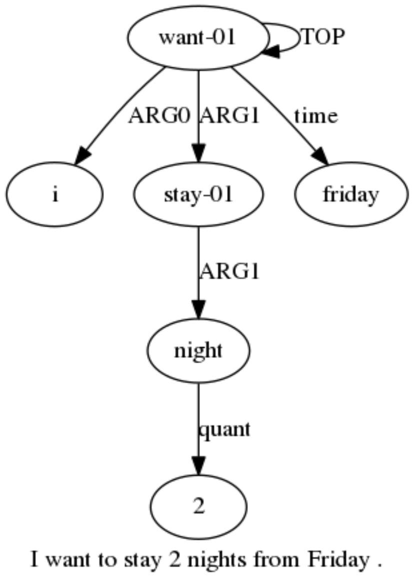
(Seneff, 1992)
https://www.aclweb.org/anthology/J92-1004



oui l'hôtel don't le prix ne dépasse pas cent dix euros

response:	oui			
refLink:	co-ref.			
	singular			
BDObject:	hotel			
		room		
		payment:	amount	
			comparative:	less
			integer:	110
			unit:	euro

(Bonneau-Maynard et al., 2005)
https://www.isca-speech.org/archive/interspeech_2005/i05_3457.html



(Damonte et al., 2017)
https://www.aclweb.org/anthology/E17-1051/

NLU basic approaches

For trees/frames/graphs:

- **grammar-based parsing**
  - handwritten/probabilistic grammars & chart parsing algorithms
- **statistical**
  - inducing structure using machine learning
  - grammar is implicit (training treebanks)

For DAs (shallow parsing):

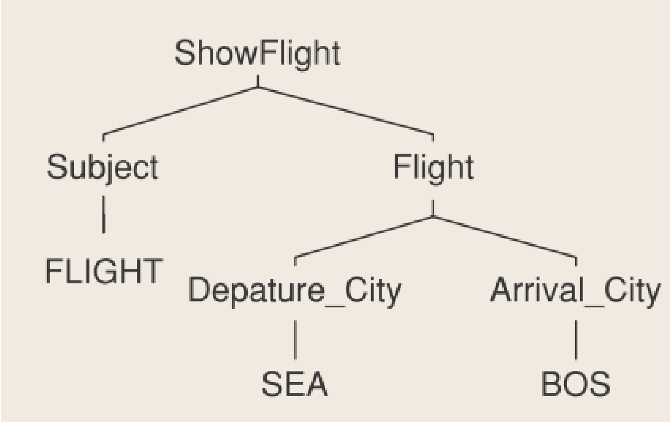
- **classification**
- **sequence labelling**
- both options can be rule-based or statistical

Grammars vs. shallow parsing

Grammars are:

- more expressive
  - hierarchical structure better captures relations
- harder to maintain
  - sparser
  - harder to build rules by hand
  - statistical parsers need more data
  - training data is harder to get
- more hardware-hungry
  - chart parsing: $O(n^3)$, shallow: $O(n)$ for simplest approaches
- more brittle
  - shallow parsing is typically less sensitive to ASR errors, variation, etc.

Show me flights from Seattle to Boston

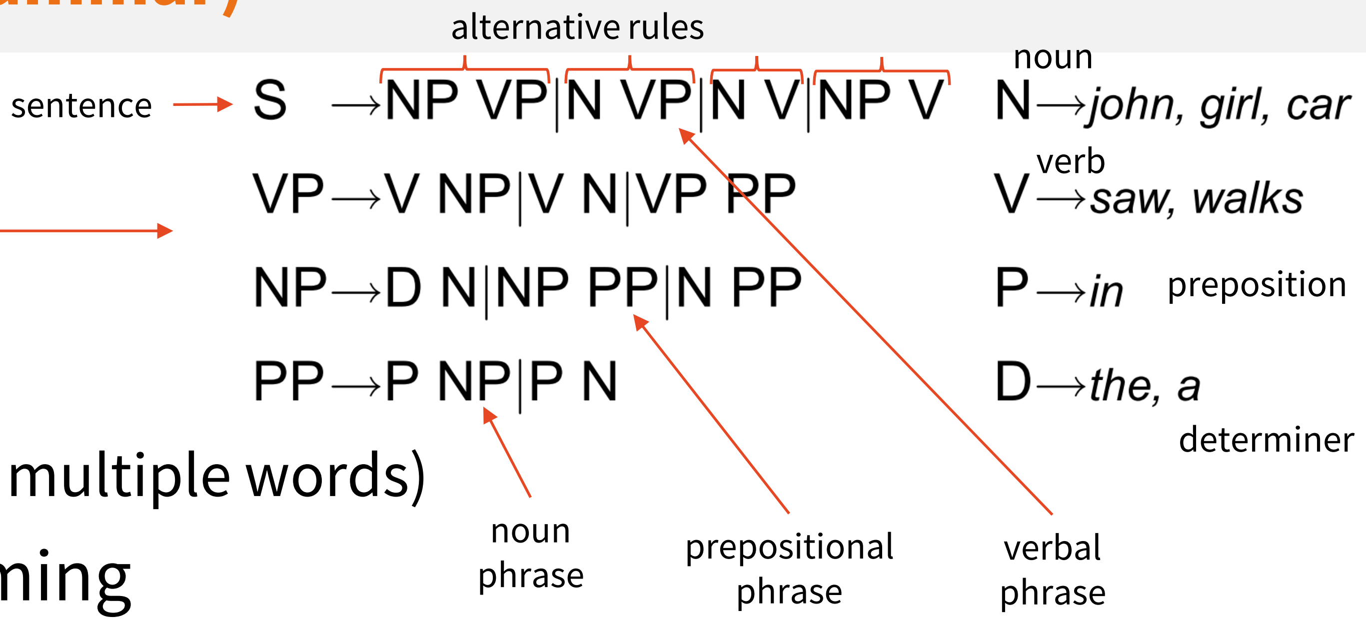


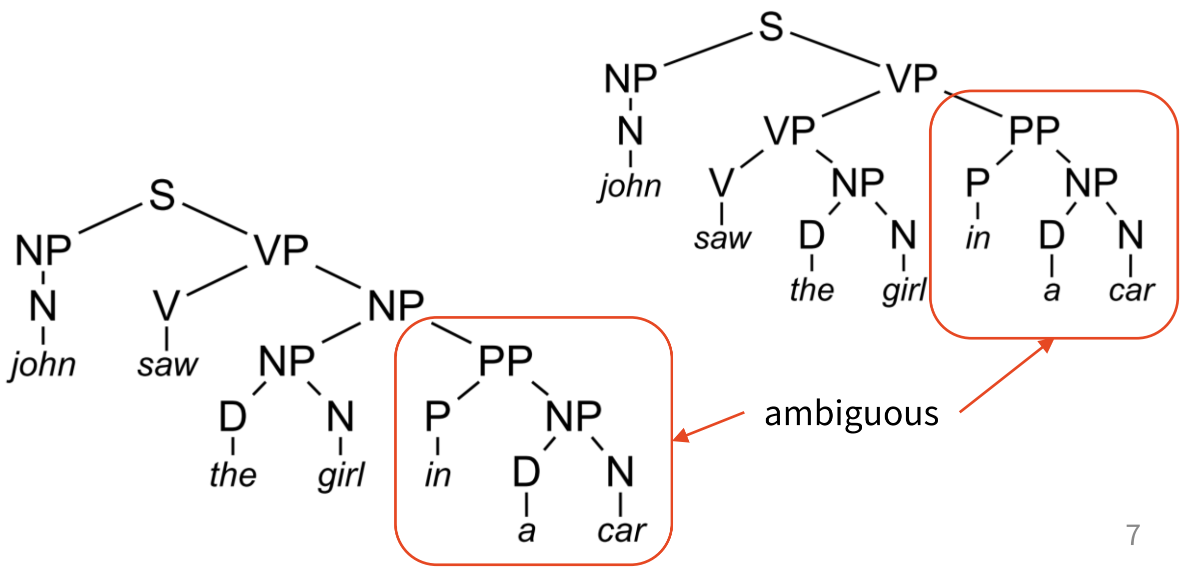
(Wang et al., 2005)
http://ieeexplore.ieee.org/document/1511821/

inform(from=SEA, to=BOS)

Grammars: CFG (Context-free Grammar)

- Simple recursive grammar
  - **rules**: X → A B C
    - splitting a phrase into adjacent parts
  - **terminals** = words
  - **non-terminals** = phrases (spanning multiple words)
- parsable using dynamic programming
  - (chart parsing)
- too simple for full natural language
  - but may be OK for a limited domain
  - especially with **probabilistic extensions**





CFG: Phoenix Parser (ATIS, 90's)

- CFG hierarchy based on semantic frames
  - Frames → slots / other frames
  - multiple CFGs, one per slot
- Robustness attempts
  - ignore stuff not belonging to any frame
- Chart parsing
  - left to right
  - maximize coverage
  - minimize # of different slots

Case Frame

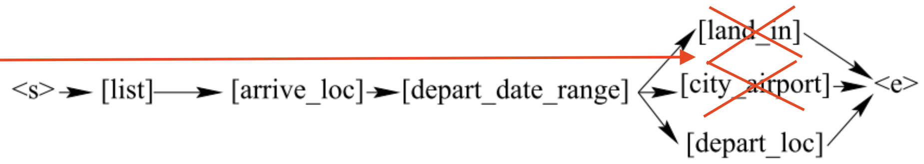
Frame: FlightInfo
Slots:
[List]
[Arrive Location]
[Depart Date Range]
[Depart Location]

[Depart Location] → LEAVE from ENT
LEAVE → leaving | departing | Ø
ENT → <city> | <airport>

I would like to | *go to Boston* | *tomorrow* | *from San Francisco*

[List] (I WOULD LIKE TO)
[Arrive Location] (GO TO [arrive_loc] ([city ([cityname] (BOSTON))))
[Depart Date Range] ([depart_date_range] ([on_date] ([date]
([day_of_week] ([dayname] (TOMORROW))))))
[Depart Location] (FROM [depart_loc] ([city] ([cityname] (SAN FRANCISCO))))

all paths matching a span are added to parse chart, they're pruned afterwards



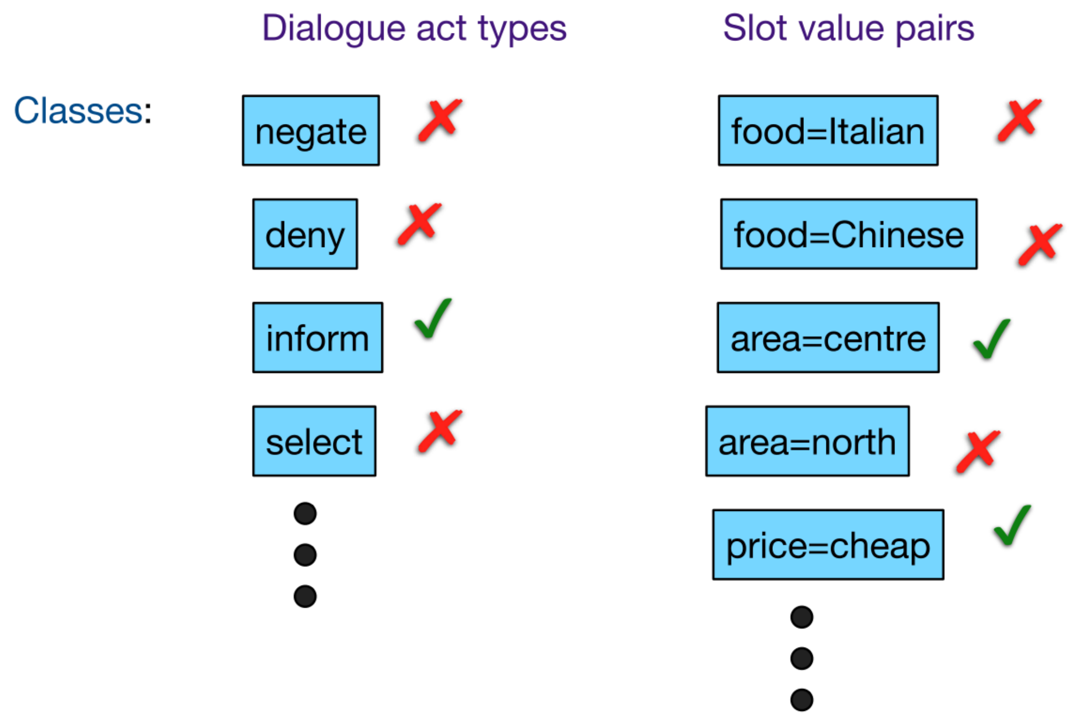
NLU as classification

- using DAs – treating them as a **set of semantic concepts**
  - concepts:
    - **intent**
    - **slot-value pair**
  - binary classification: is concept Y contained in utterance X?
  - independent for each concept
- consistency problems
  - conflicting intents (e.g. *affirm* + *negate*)
  - conflicting values (e.g. *kids-allowed=yes* + *kids-allowed=no*)
  - need to be solved externally, e.g. based on classifier confidence

NLU as classification

- classification:
  features → labels (classes)
  - here: classes are **binary** (-1/1 or 0/1)
  - **one classifier per concept**
- features
  - **binary – is X present?**
    or **count – how many X's are present?**
  - words
  - n-grams
  - word pairs/triples
    (position-independent)
  - regex
  - presence of named entities

I'm looking for something cheap in the city centre.



(from Milica Gašić's slides)

NER + delexicalization

What is the phone number for Golden Dragon?
*What is the phone number for **<restaurant-name>**?*

I’m looking for a Japanese restaurant in Notting Hill.
*I’m looking for a **<food>** restaurant in **<area>**.*

Approach:

1) **identify** slot values/named entities
2) **delexicalize** = replace them with placeholders (indicating entity type)
   - or add the NE tags as more features for classification

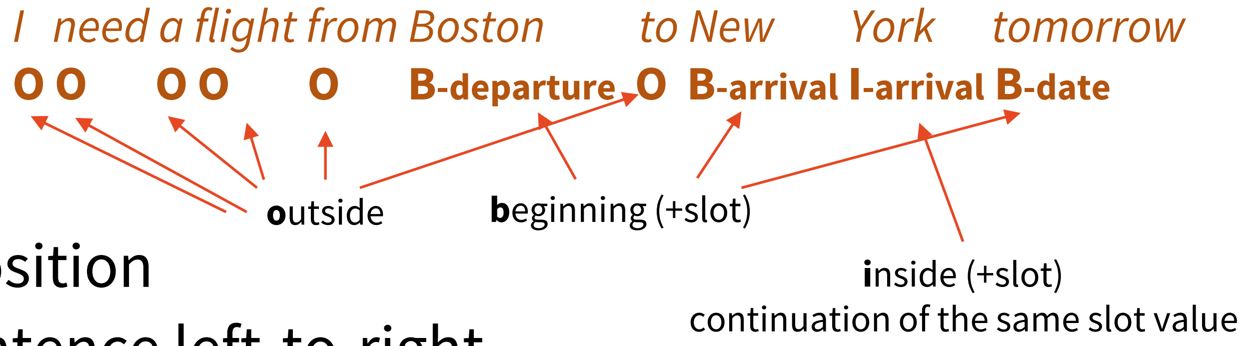
- generally needed for NLU as classification
  - otherwise in-domain data is too sparse
  - this can vastly reduce the number of concepts to classify & classifiers
- NER is a problem on its own
  - but general-domain NER tools may need to be adapted
    - added gazetteers with in-domain names
  - in-domain gazetteers alone may be enough
  - NE supplemented by NE linking/disambiguation (usually not needed in DS)

NLU Classifiers

- note that data is usually scarce!
- **handcrafted / rules**
  - simple mapping: word/n-gram/regex match → concept
  - can work really well for a limited domain
  - no training data, no retraining needed (tweaking on the go)
- **logistic regression**
- **SVM** (support vector machine)
- **neural nets**
  - different, “automatic” features (embeddings, see later)
  - only applicable if a lot of data is available

Slot filling as sequence tagging

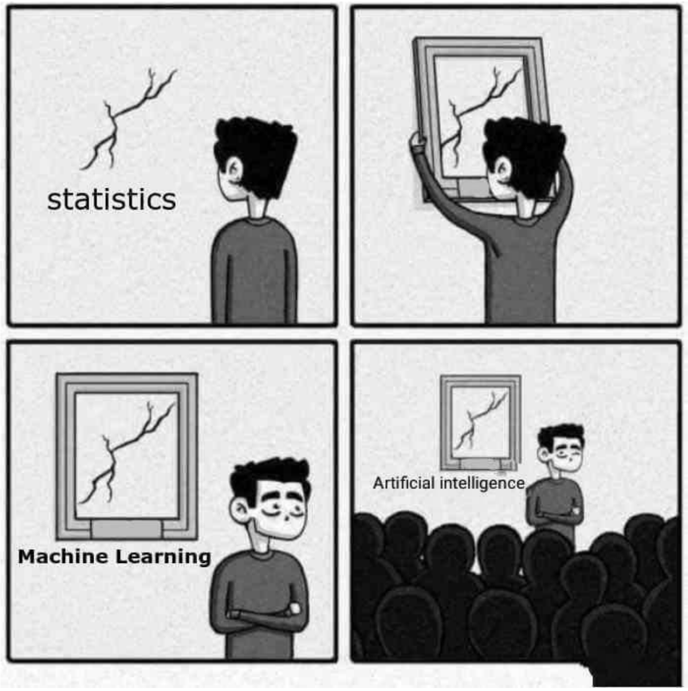
- get slot values directly – "automatic" delexicalization
  - each word classified
  - classes = slots & **IOB format** (inside-outside-beginning)
  - slot values taken from the text
    (where a slot is tagged)
  - NER-like approach
- rules + classifiers kinda still work
  a) keywords/regexes found at specific position
  b) apply classifier to each word in the sentence left-to-right
  - problem: overall consistency
    - slots found elsewhere in the sentence might influence what's classified now
- solution: **structured/sequence prediction**
  - HMM, MEMM, CRF…



Machine Learning (Grossly Oversimplified)

ML is basically function approximation

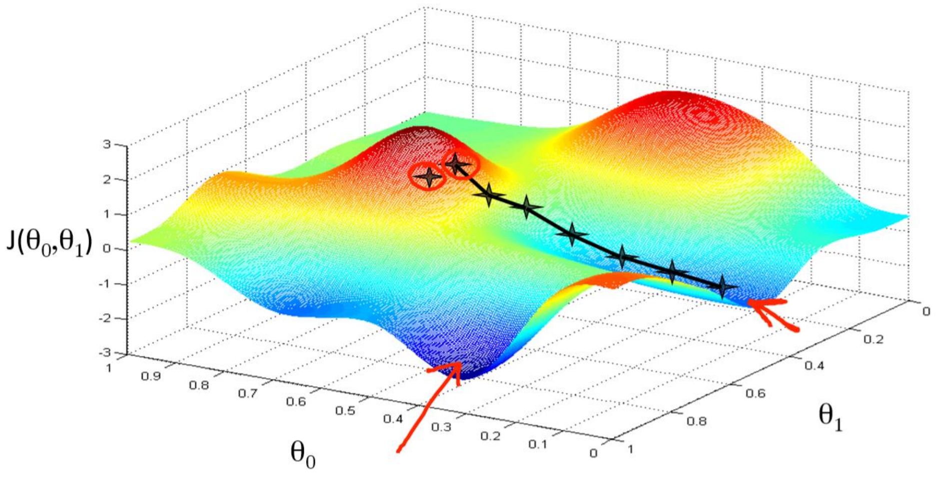
- function: data (**features**)→ **labels**
  - discrete labels = **classification**
  - continuous labels = **regression**
- function shape
  - this is where different algorithms differ
  - neural nets: complex functions, composed of simple building blocks (linear, sigmoid, tanh…)
- **training/learning** = adjusting function parameters to minimize error
  - **supervised** learning = based on data + labels given in advance
  - **reinforcement** learning = based on exploration & rewards given online



https://towardsdatascience.com/no-machine-learning-is-not-just-glorified-statistics-26d3952234e3

Machine Learning (Grossly Oversimplified)

- training– **gradient descent** methods
  - minimizing a **cost/loss function**
    (notion of error – given system output, how far off are we?)
  - calculus: derivative = steepness/slope
  - follow the slope to find the minimum – derivative gives the direction
  - **learning rate** = how fast do we go (needs to be tuned)
- gradient typically computed over **mini-batches**
  - random bunches of a few training instances
  - not as erratic as using just 1 instance,
    not so slow as computing over whole data
  - **stochastic gradient descent**
  - improvements: AdaGrad, Adam […]
    - cleverly adjusting the learning rate



https://hackernoon.com/gradient-descent-aynk-7cbe95a778da

Digression: Generative vs. Discriminative Models

What they learn:

- **Generative** – whole distribution $p(x, y)$
- **Discriminative** – just decision boundaries between classes ~ $p(y|x)$

To predict $p(y|x)$…

- **Generative models**
  - Assume some functional form for $p(y), p(x|y)$
  - Estimate parameters of $p(y), p(x|y)$ directly from training data
  - Use Bayes rule to calculate $p(y|x)$
- **Discriminative models**
  - Assume some functional form for $p(y|x)$
  - Estimate parameters of $p(y|x)$ directly from training data

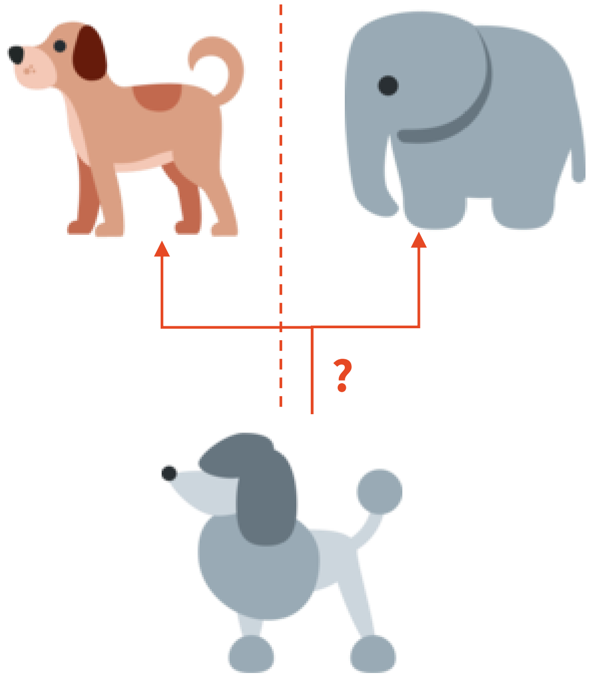
they get the same thing, but in different ways

https://medium.com/@mlengineer/generative-and-discriminative-models-af5637a66a3

Generative vs. Discriminative Models

Example: elephants vs. dogs http://cs229.stanford.edu/notes/cs229-notes2.pdf

- **Discriminative**:
  - establish decision boundary (~find distinctive features)
  - classification: just check on which side we are
- **Generative**
  - ~ 2 models – what elephants & dogs look like
  - classification: match against the two models

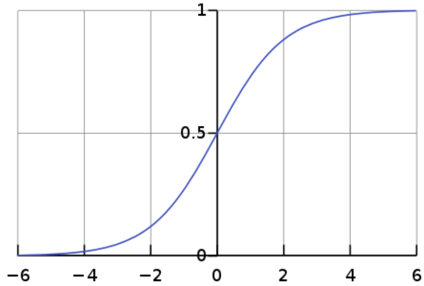


- Discriminative – typically better results
- Generative – might be more robust, more versatile
  - e.g. predicting the other way, actually generating likely (x, y)'s

Logistic Regression (LR, also called Maximum Entropy Classifier)

- modeling using the sigmoid (logistic) function with parameters $\boldsymbol{\theta}$

sigmoid



target class is binary, i.e. $y \in \{-1, +1\}$

$$p(y|\mathbf{x}) = \text{sigmoid}(-y(\boldsymbol{\theta} \cdot \mathbf{x})) = \frac{1}{1 + \exp(-y(\boldsymbol{\theta} \cdot \mathbf{x}))}$$

input data/features

equivalent form
– maximum entropy style
(works for **multiclass**, too!)

$$p(y|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}, y))$$

normalization

generalization: **feature functions** vector
(some fire for each value of y)

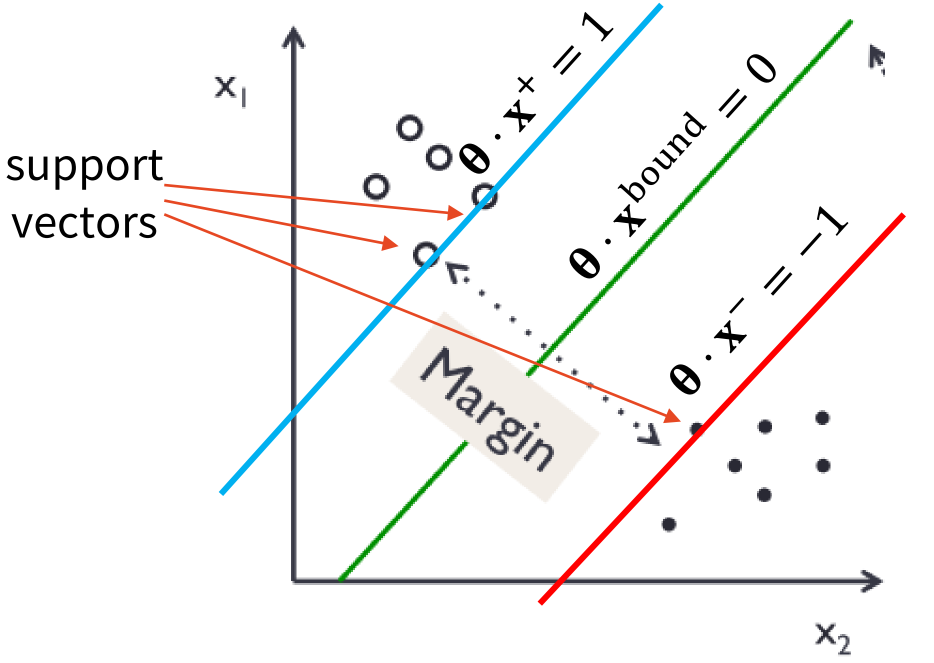
- despite the name, it's a classifier
- very basic, but powerful with the right features
- trained by gradient descent (logistic/cross entropy loss)
- maximum entropy estimate ("most uniform model given data")

$y \in \{0,1\}$ vs. $\{-1, +1\}$: https://stats.stackexchange.com/questions/229645/
formula equivalence: http://ufal.mff.cuni.cz/~odusek/var/upload/docs/msc_thesis.pdf, page 30

Support-Vector Machines (SVMs)

- geometric intuition: features ~ coordinates in multidimensional space
- trying to separate classes with a hyperplane (**decision boundary**)
- idea: let's find a boundary with **maximum margin**
  - i.e. maximize distance between classes → best generalization
    - most likely to classify new example correctly
  - this boundary is given by **support vectors** (instances that are closest to it)
- margin width is $\frac{2}{||\boldsymbol{\theta}||}$ → we minimize $||\boldsymbol{\theta}||^2$
- SVM score: $g(\mathbf{x}) = \boldsymbol{\theta} \cdot \mathbf{x}$
  - 0 at the boundary, +1/-1 for support vectors
  - sign of the score gives the class (positive/negative)

(from Aikaterini Tzompanaki's slides)



x_1, x_2 = features

o = positive class

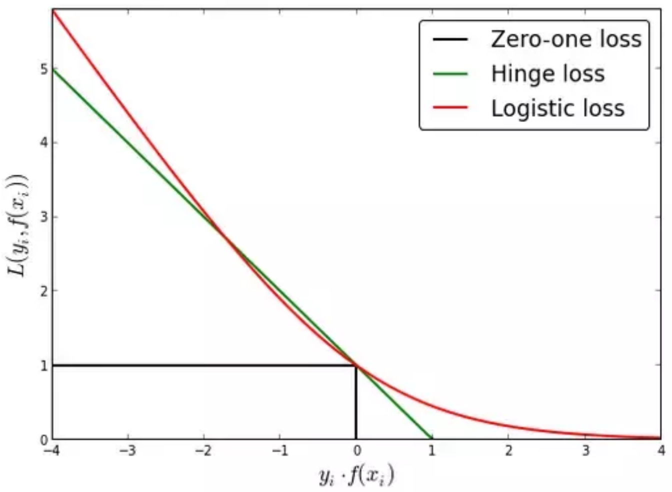
• = negative class

why margin is $\frac{2}{||\boldsymbol{\theta}||}$: https://math.stackexchange.com/questions/1305925/

SVM vs. Logistic Regression

- **soft-margin SVM** – for non-separable cases
  - non-separable = messy data, can't separate with a hyperplane
  - "soft" = weighing correct classification (**hinge loss**) & margin size
  - model: $\min_{\boldsymbol{\theta}} \lambda ||\boldsymbol{\theta}||^2 + \sum_i \max\{0, 1 - y_i \boldsymbol{\theta} \cdot \mathbf{x}_i\}$

regularization weight



- **regularized logistic regression** – for better generalization
  - preventing overfitting to training data – trying to keep parameter values low
  - **logistic loss**
  - model: $\min_{\boldsymbol{\theta}} \lambda ||\boldsymbol{\theta}||^2 + \sum_i \log(1 + \exp(1 - y_i \boldsymbol{\theta} \cdot \mathbf{x}_i))$
- the main difference is the loss form
  - hinge loss should be marginally better for classification, but it depends

https://gdcoder.com/support-vector-machine-vs-logistic-regression/

Classification example

features ($\mathbf{x}$)

I	1
want	1
to	3
go	1
from	2
<airport-1>	1
…	
him	0
price	0
tell	0
…	
I want	1
want to	1
to go	1
….	
from <airport-1>	1

ASR: *I want to go from from Newark to London City next Friday*
Delex: *I want to go from from <airport-1> to <airport-2> next <day-1>*

weights:

intent=search_flights	$\boldsymbol{\theta}_{SF}$
intent=request_price	$\boldsymbol{\theta}_{RP}$
…	
from_airport=<airport-1>	$\boldsymbol{\theta}_{FA1}$
….	

weights define different classifiers

SVM: $\boldsymbol{\theta}_{FA1} \cdot \mathbf{x} = +3.4347$ → found from_airport=Newark
LR: $\text{sigmoid}(\boldsymbol{\theta}_{FA1} \cdot \mathbf{x}) = 0.883$ → found from_airport=Newark (conf. = 0.883)

Maximum Entropy Markov Model (MEMM)

- Looking at past classifications when making next ones
  - LR + a simple addition to the feature set
- Whole history would be too sparse/complex
  → **Markov assumption**: only the most recent matters
  - 1st order MM: just the last one (←this is what we show here)
  - *n*th order MM: *n* most recent ones
- still not modelling the sequence globally

$$p(\mathbf{y}|\mathbf{x}) = \prod_{t=1}^{T} \frac{1}{Z(y_{t-1}, \mathbf{x})} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(y_t, y_{t-1}, \mathbf{x}))$$

looking at the whole input

for the whole sequence

time steps are independent except for y_{t-1}

y_{t-1} is the main addition compared to LR

Hidden Markov Model (HMM)

- Modelling the **sequence as a whole**
- Very basic model:
  - “**tag depends on word + previous tag**”
- Markov assumption, again
- “Hidden” – reverse viewpoint:
  - “tags are hidden, but they influence the words on the surface”
- Inference – Viterbi algorithm
  - we can get the **globally best tagging**

HMM is a **generative model** – models **joint distribution** $p(\mathbf{y}, \mathbf{x})$, not just conditional $p(\mathbf{y}|\mathbf{x})$

$$p(\mathbf{y}, \mathbf{x}) = \prod_{t=1}^{T} p(y_t | y_{t-1}) p(x_t | y_t)$$

for the whole sequence

transition probability prev. tag → tag

observation probability tag → word

HMM vs. MEMM

- MEMM:
  - any feature functions, as in LR
  - local normalization – does not model whole sequences, just locally
  - **label bias** problem
    - training: you know the correct labels
    - inference: one error can lead to a series of errors
- HMM:
  - global normalization for $p(\mathbf{y}|\mathbf{x})$ over all $\mathbf{y}'$s
    - modelling sequences as a whole
  - **very** boring & **limited** feature functions
- how about best of both?

Linear-Chain **Conditional Random Field (CRF)**

- HMM + more complex feature functions
- MEMM + global sequence modelling

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \prod_{t=1}^{T} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(y_t, y_{t-1}, \mathbf{x}))$$

global normalization (otherwise like MEMM)

feature functions looking at whole input (otherwise looks like HMM)

- state-of-the art for many sequence tagging tasks (incl. NLU)
  - until NNs took over
  - used also in conjunction with NNs
- global normalization makes it slow to train

Sequence tagging example

ASR: *I want to go from from Newark to London City next Friday*

Previous tags: **O O O O O O B-from_airport O**

current position: what's the class for *London*?

features ($\mathbf{x}$):

in_sent=I	1	*cur*=London	1	*prev_tag*=O	1
in_sent=want	1	*cur*=him	0	*prev_tag*=B-price	0
in_sent=to	3	…		…	
in_sent=go	1	*prev*=to	1		
…		*prev*=want	0		
in_sent=him	0	*prev*=price	0		
in_sent=price	0	…			
…		*cur*=to London	1		
in_sent=I want	1	*prev*=Newark to	1		
in_sent=want to	1	…			
in_sent=to go	1				

using y_{t-1}

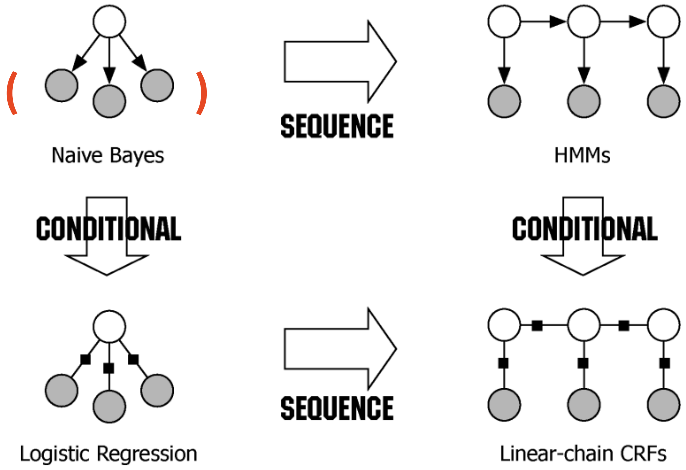
HMM considers only these

MEMM: looks at *London*, ignores that it also needs to tag *City* later → likely to tag as B-to_city

CRF: also considers future tags, more likely to tag *London City* as B-to_airport I-to_airport

Summary

- NLU can be tricky
  - bad grammar, fragments, synonymy, ASR errors …
- Grammars, frames, graph representation
  - rule-based or statistical structure induction
  - more expressive, but harder – not so much in limited-domain systems
- Shallow parsing
  - dialogue acts: intent + slots & labels
  - rules – keyword spotting, regex
  - classification (LR, SVM)
  - sequence tagging (MEMM, HMM, CRF)
- Coming up: neural NLU & dialogue state tracking



(Sutton & McCallum, 2010)
https://arxiv.org/abs/1011.4088

Thanks

Contact us:

https://ufaldsg.slack.com/
odusek@ufal.mff.cuni.cz
Skype/Meet/Zoom (by agreement)

Labs at 3:40pm

Get the slides here:

http://ufal.cz/npfl123

References/Inspiration/Further:

- Milica Gašić’s slides (Cambridge University): http://mi.eng.cam.ac.uk/~mg436/teaching.html
- Raymond Mooney’s slides (University of Texas Austin): https://www.cs.utexas.edu/~mooney/ir-course/
- Filip Jurčíček’s slides (Charles University): https://ufal.mff.cuni.cz/~jurcicek/NPFL099-SDS-2014LS/
- Hao Fang’s slides (University of Washington): https://hao-fang.github.io/ee596_spr2018/syllabus.html
- Aikaterini Tzompanaki’s slides (University of Cergy-Pontoise): https://perso-etis.ensea.fr/tzompanaki/teaching.html
- Pierre Lison’s slides (University of Oslo): https://www.uio.no/studier/emner/matnat/ifi/INF5820/h14/
- Sutton & McCallum – Introduction to Conditional Random Fields: https://arxiv.org/abs/1011.4088
- Andrew McCallum’s slides (U. of Massatchusets Amherst): https://people.cs.umass.edu/~mccallum/courses/inlp2007/

Hidden Markov Model vs. MEMM (additional explanation, just FYI, not required)

- Rewrite HMM so it looks more like MEMM + get conditional probability

just indicators (binary features)

transition

observation

hide the actual probabilities as weights (in logarithm)

$$p(\mathbf{y},\mathbf{x}) = \prod_{t=1}^{T} \exp\Big(\sum_{i,j\in S} \theta_{ij} 1_{y_t=i} 1_{y_{t-1}=j} + \sum_{i\in S}\sum_{o\in O} \mu_{oi} 1_{y_t=i} 1_{x_t=o}\Big)$$

subsume transition & observation under **feature functions**, θ_k is θ_{ij} & μ_{oi}

$$p(\mathbf{y},\mathbf{x}) = \prod_{t=1}^{T} \exp\Big(\sum_{k=1}^{K} \theta_k f_k\,(y_t, y_{t-1}, x_t)\Big)$$

just the current word

conditional probability:

$$p(\mathbf{y}|\mathbf{x}) = \frac{p(\mathbf{y},\mathbf{x})}{\sum_{y'} p(\mathbf{y}',\mathbf{x})} = \frac{1}{Z(\mathbf{x})} \prod_{t=1}^{T} \exp\left(\sum_{k=1}^{K} \theta_k f_k(y_t, y_{t-1}, x_t)\right) = \frac{1}{Z(\mathbf{x})} \prod_{t=1}^{T} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(y_t, y_{t-1}, x_t))$$

vector notation

normalization is global