COMP4650 / COMP6490
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Introduction

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Overview of IE lectures

- Introduction to Information Extraction (IE)
- Sequence labeling methods
  - Markov Process
  - The HMM algo
  - The CRF algorithm
- Automatic summarization

* Acknowledgement: Some of the content originates from the Stanford NLP course at Coursera.org

Sequence labeling

Sequential data

- Speech, text, video analysis, time-series, stock market, genes...

Sequential la

- Is a type of patt volves the algorithmic assignment of a categorical lab ember of a sequence of observed values

Sequential methods

- Probabilistic methods; usually make a Markov assumption
- Algorithms: HMM, Maximum Entropy, Conditional Random Fields

Sequence labeling in NLP

speech recognition

part-of-speech tagging

sentence seg

grapheme to tion

chunking (shallow synta ing)

named entity recogntion

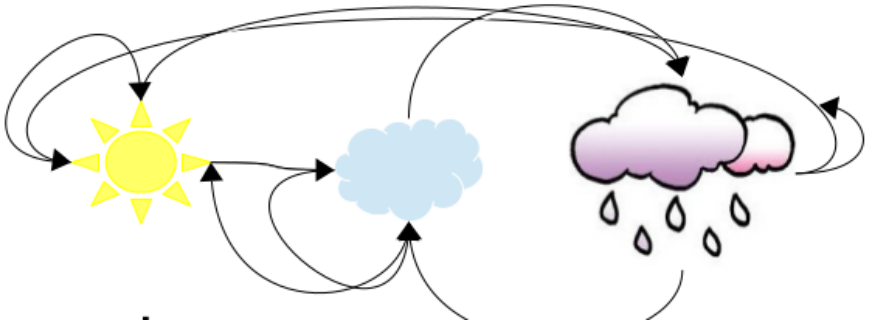
information extraction

Markov Process

Deterministic patterns

- Each state is dependent solely on the previous state
- Easy to understand and determine once the transitions are fully known, e.g., semaphore

Andrei Andreyevich Markov
1856-1922



Non deterministic patterns

- It is possible for any state to follow another, e.g., weather

Markov chain

Stochastic m e of possible events
in which the epends only on the
state attained in the previous

First-order Markov chain, t particular state
dependes only on the previous state

Markov assumption

$$P(q_i = a | q_1 \ldots q_{i-1}) = P(q_i = a | q_{i-1})$$

A **Markov chain**: compute a prob. for a sequence of events that we can be observe in the world.

But some events are not observable in the world…

Hidden Markov model

Hidden Markov Model

Markov assumption

$$P(q_i = a | q_1 \ldots q_{i-1}) = P(q_i = a | q_{i-1})$$

Output indepe prob of an output observation o_i depends only on at produce the observation q_i and not on any r any other observations

$$P(o_i | q_1 \ldots q_i, \ldots, q_T, o_1, \ldots, o_i, \ldots, o_T) = P(o_i | q_i)$$

Weather and Ice Cream

Jason Eisner, 2002

- You are a climatologist in the year 2799 studying global warming
- You can't find an in Baltimore for summer of 2018
- But you find JE's diary
- Which lists how many ice-creams Jason ate every day that summer
- Use the observations (ice-cream ate) to estimate the temperature every day

Hidden Markov Model

Various examples exist where the process states are not directly observable, but are indirectly observable,

then we have a **Hidden Markov Model**

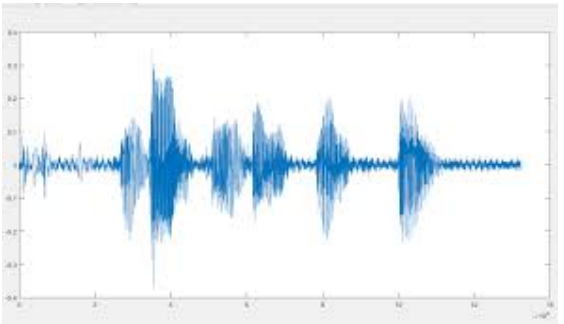
DT NN

The house is ré

Hidden states

Observations

The house is red.

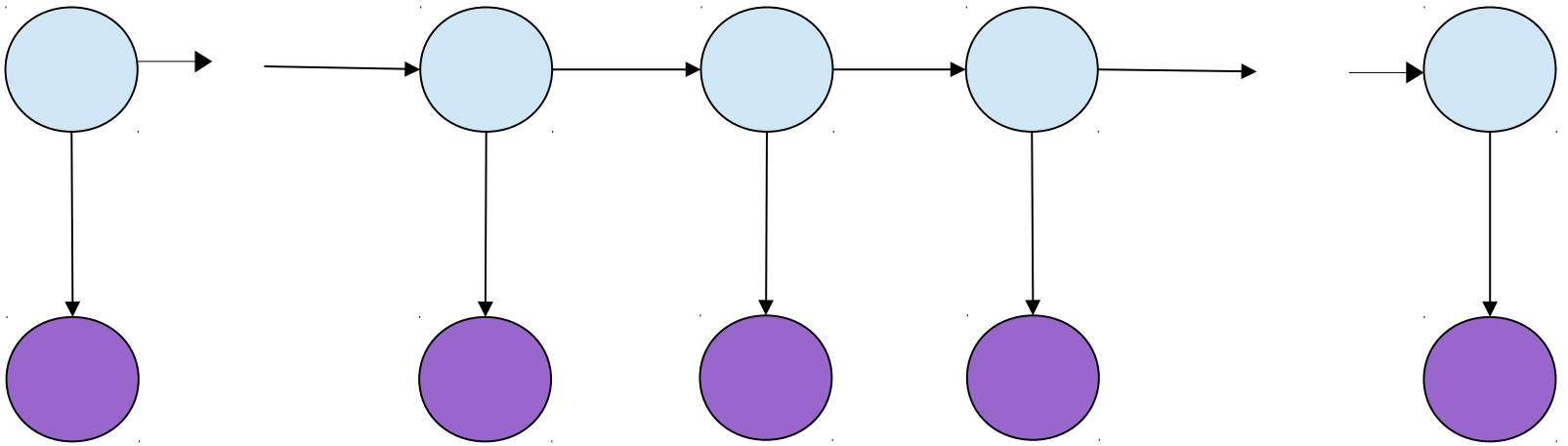


Hidden states

Observations

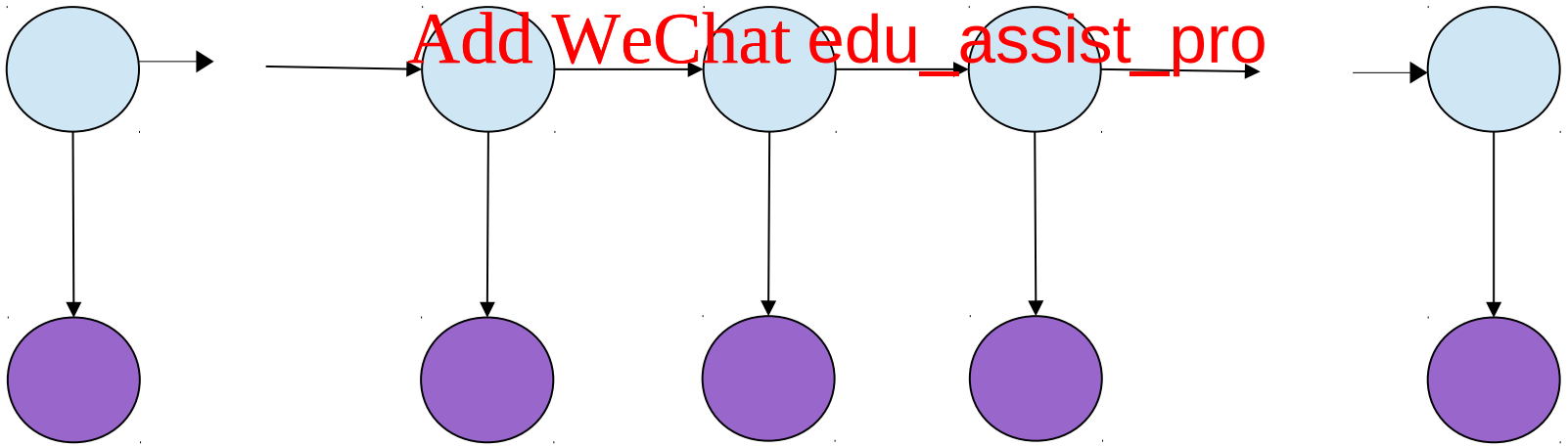
What is a Hidden Mark Model?

- HMM is a graphical model
- Circles represent states
- Arrows represent probabilistic dependencies between states



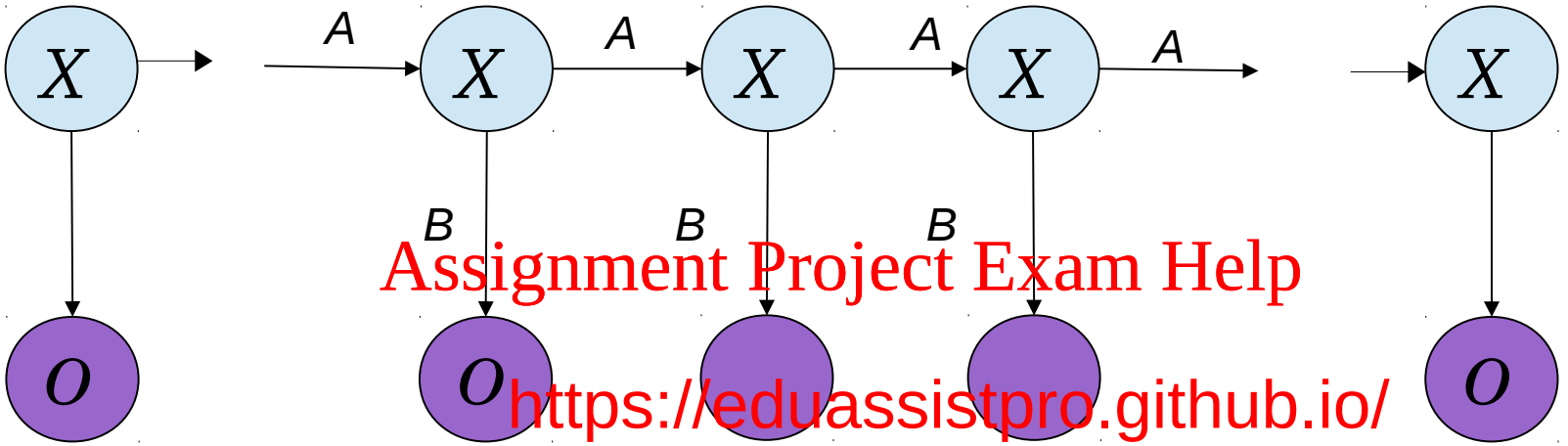
HMM Notation

- **Light blue nodes** are **hidden states**
  - Dependent only on the previous state
- **Purple nodes** are **observations states**
  - Dependent only

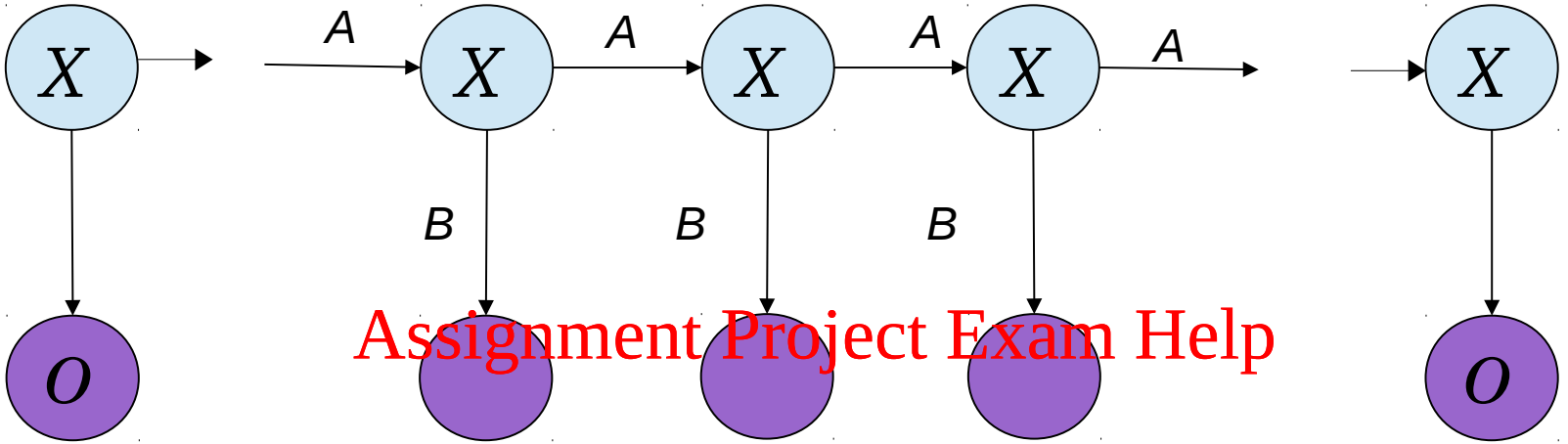


The future is independent of the past, given the present

HMM notation



HMM model $\mu=(A,B,\pi)$



HMM Problems

There are three fundamental problems that can be solved using HMM

1. **LIKELIHOOD** (testing)**:** Given an HMM model $\mu=(A,B,\pi)$ and an observation sequence ***O,*** compute the likelihood ***P*(*O*|μ)**.

   Given # ice-creams, what is the weather?

2. **DECODING:** Given an o del $\mu=(A,B,\pi)$, discover the best hidden state sequence ***Q****.*

   Given a sequence of ice-creams, what was the most likely weather on those days?

3. **LEARNING:** Given an observation sequence ***O*** and set of possible states in the HMM, learn the HMM parameters ***A*** and ***B***.

Likelihood

Likelihood: Given an HMM λ = (A,B) and an observation sequence O, determine the likelihood P(O, λ)

- E.g. what is the probability of ice-cream sequence 3 – 1 – 3?

- But we don't know what the hidden state sequence is...

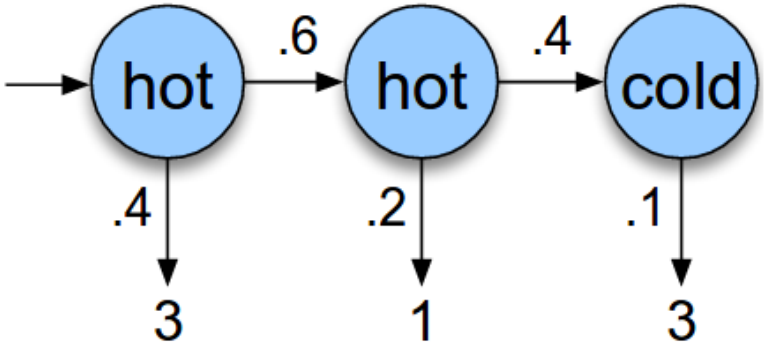
Likelihood

Let's make it simpler.

What is the likelihood of an ice-cream observed sequence 3-1-3, given the hidden state sequence *HOT HOT COLD?*

$$P(3\ 1\ 3|\text{hot hot cold}) = P(3|\text{hot}) \times P(1|\text{hot}) \times P(3|\text{cold})$$

Likelihood



Join prob. Of been in a particular weather sequence Q and generate a particular sequence of ice-creams events

$$P(3\ 1\ 3, \text{hot hot cold}) = P(\text{hot}|\text{start}) \times P(\text{hot}|\text{hot}) \times P(\text{cold}|\text{hot}) \times P(3|\text{hot}) \times P(1|\text{hot}) \times P(3|\text{cold})$$

Likelihood

Compute the prob. of ice-cream events 3-1-3 by summing over all possible weather sequences, weighted by their probability

For N hidden states and observation sequence of T observations, there are N^T possible hidden state sequences.

When N and T are large → intractable

Likelihood → Forward algorithm

Dynamic Programming algorithm, stores table of intermediate values so it need not recompute them.

Computes P(O) by summing over probabilities of all hidden state paths that could generate the observation sequence 3-1-3:

The previous forward path probability

The transition probability from the previous state to the current state α_{ij}

The state observation likelihood of the observation o_t given the current state j $b_j(o_t)$

HMM Problems

1. **LIKELIHOOD** (testing)**:** Given an HMM model $\mu=(A,B,\pi)$ and an observation sequence ***O,*** compute the likelihood ***P*(*O*|μ)**.

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Decoding: Viterbi algorithm

(Andrew Viterbi, 1967)

Decoding: Given an observation sequence *O* and an HMM $\lambda = (A,B)$, discover the ***best*** hidden state sequence of weather states in *Q*

Given the observatio *M, what is the **best** (most probable) hidd* {H, C}

Viterbi algorithm

- Dynamic programming algorithm
- Uses a dynamic programming trellis to store probabilities that the HMM is in state *j* after seeing the first *t* observations, for all states *j*

Decoding: Viterbi algorithm

Decoding: Given an observation sequence *O* and an HMM $\lambda = (A,B)$, discover the ***best*** hidden state sequence of weather states in *Q*

Given the observatio *M, what is the* ***best*** *(most probable) hidd* {*H, C*}

Viterbi algorithm

- Dynamic programming algorithm
- Uses a dynamic programming trellis to store probabilities that the HMM is in state *j* after seeing the first *t* observations, for all states *j*

- Value in each cell computed by taking MAX over all paths leading to this cell – i.e. best path

- Extension of a path from state i at time t-1 is computed by multiplying:

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t)$$

- Most probable path is the max over all possible previous state sequences

Like Forward Algorithm, but it takes the max over previous path probabilities rather than sum

Viterbi example

HMM model was develop by Baum and collegues in Princeton (Baym and Petrie, 1966; Baum and Eagon, 1967)

Viterbi

Multiple independent discovery and publications

Andrea Giacomo Viterbi, 1935 (age 83)

HMM Problems

There are three fundamental problems that can be solved using HMM

1. **LIKELIHOOD** (testing)**:** Given an HMM model $\mu=(A,B,\pi)$ and an observation sequence ***O,*** compute the likelihood ***P*(*O*|μ)**.

   Given # ice-creams, what is the weather?

2. **DECODING:** Given an o del $\mu=(A,B,\pi)$, discover the best hidden state sequence ***Q***.

   Given a sequence of ice-creams, what was the most likely weather on those days?

3. **LEARNING/TRAINING:** Given an observation sequence ***O*** and set of possible states in the HMM, learn the HMM parameters ***A*** and ***B***.

Training: The Forward-Backward (Baum-Welch) Algorithm

- ***Learning***: Given an observation sequence O and the set of states in the HMM, learn the HMM param nd B (emission)

- Input: unlabeled seq of o ns O and vocabulary of possible hidden states Q
  - E.g. for ice-cream weather:
    - Observations = {1,3,2,1,3,3,…}
    - Hidden states = {H,C,C,C,H,C,….}

- Intuitions
  - Iteratively re-estimate counts, starting from an initialization for A and B probabilities, e.g. all equi-probable
  - Estimate n… omputing forward pr… rvation, dividing prob. mass among all … tributing to it, and computing the backward probability from the same state

Details: https://web.stanford.edu/~jurafsky/slp3/A.pdf

POS-tagging with HMM

Summary

- HMMs are a major tool for relating observed sequences to hidden information that explains or predicts the observations
- Forward, Viterbi, and Forward-Backward Algorithms for computing likelihoods, decoding, and training HMMs

The power of HMMs

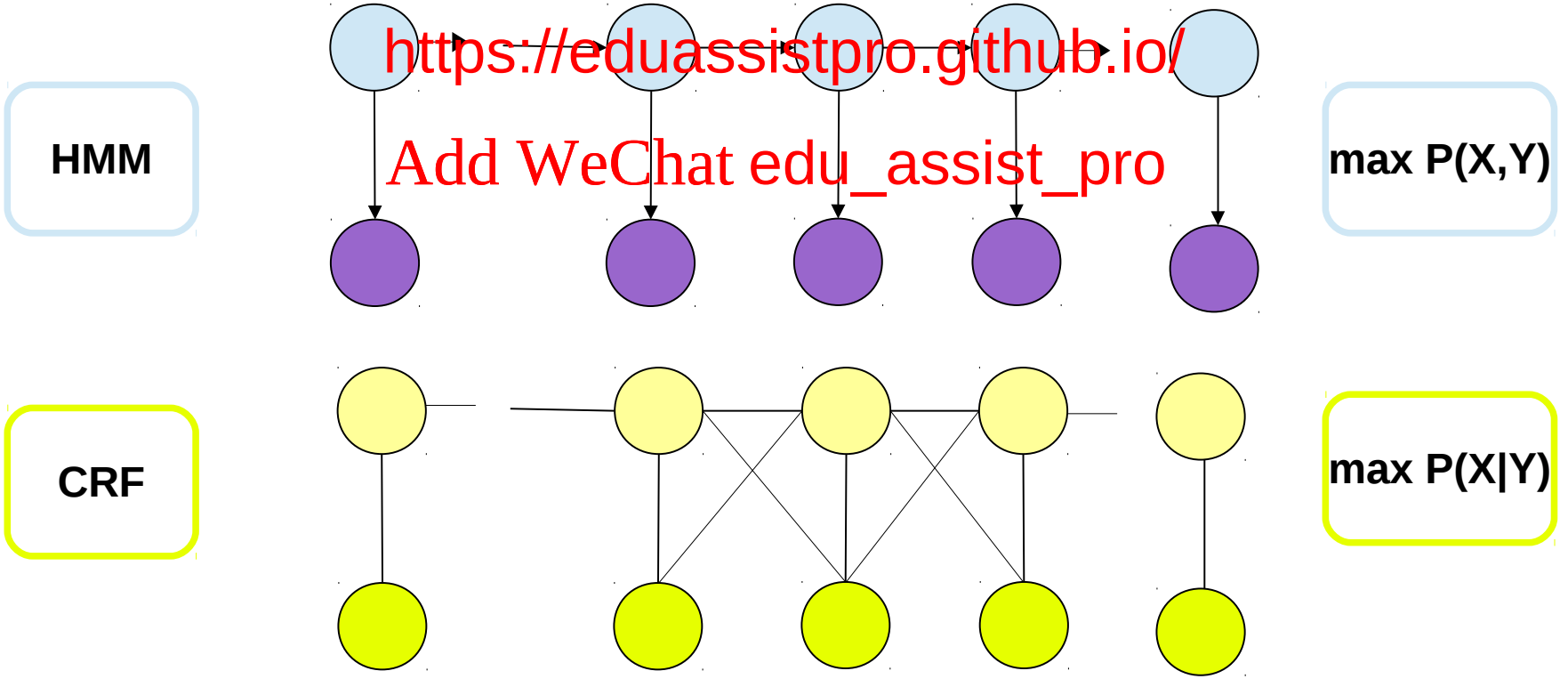
We can use the special structure of this model to do a lot of neat math and solve problems that are otherwise not solvable!!

- **NLP applications**
  - Speech Recognition
  - POS-Tagging
  - Information Extraction
  - Word/clause segment
- **Other applications**
  - Gene finding
  - Robot localization
  - User modeling

- **Limitations**
  - Local features
  - Simple HMM models do not work well with large data
  - Difficult to incorporate a diverse set features
  - No suited to work with long distance dependencies (up to ~3/5 grams)

Conditional Random Fields (CRF)

- CRF is a graphical model (Lafferty, McCallum, and Pereira, 2001)
- Relax the strong independence assumptions made in models such as HMM
- The biggest advantage of CRFs over HMMs is that they can handle ***overlapping features***



HMM vs. CRF

HMM

- Trained by maximizing likelihood of data and class *p(x, y)*
- Features are a independent
- Feature weights set independently
- Normalization is per state

CRF

- Trained by maximizing conditional likelihood of *p(x|y)*
- dency on features
  count by feature
- Feature weights are set mutually
- Normalization over the whole sequence

Take away

Sequential data

- Speech, text, video analysis, time-series, stock market, genes…

Sequential labeling problem

- Is a type of pattern recognition task that involves the algorithmic assignment of a categorical label to each member of a sequence of observed values

Sequential methods

- Probabilistic methods; usually make a Markov assumption, i.e. that the choice of label directly dependent only on the immediately adjacent labels;
- Algorithms: HMM, Maximum Entropy, Conditional Random Field

Markov Process are the basics for:

Reinforcement learning; Planing; RNN; Sequence2Sequence models, etc.

Anecdotal References

Markov Chains

https://www.youtube.com/watch?v=o-jdJxXL_W4

HMM 3D Simulator

https://www.youtube.com/watch?v=Fy6tLBzXT4M

HMM @ Numb3rs: Find a m

https://www.youtube.com/watch?v=RFCMoQ4

Viterbi algorithm @ Numb3rs: predict the next a inal

https://www.youtube.com/watch?v=NdOm8NE0qD4

They always say practice makes perfect

HMM in Python, with scikit-learn

https://github.com/hmmlearn/hmmlearn

UMDHMM

http://www.kanungo.com/software/software.html#umdhmm

CRFsuite Python

http://www.chokkan.org/software/crfsuite/

CRF++ C++

http://crfpp.googlecode.com/svn/trunk/doc/index.html

GRMM Java

http://mallet.cs.umass.edu/grmm/index.php

Further References

Stamp, 2012. ***A Revealing Introduction to Hidden Markov Models***.

Lafferty, McCallum and Pereira, 2001. ***Conditional Random Fields: Probabilistic Models for S quence Data***.

Sutton and McCallum, 2006. ***An Introduction I Random Fields for Relational Learning***.

Bikel, 1999. ***An Algorithm that Learns What's in a Name***.

Bach and Badaskar, 2007. ***A survey on Relation Extraction.***