ML for Speech Processing (includes Paralinguistic Speech Processing)

Dr. Mathew Magimai Doss

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Outline

Outline

Machine learning

- Learning is an essential part of living
- Learning typically means changing/adapting to be better, as per a given criterion, when a similar situation arrives
- Challenge lies in generalizing to new or unobserved situations

Challenge

- Learning needs training data. We have access to only a finite amount of training data.
- Variabilities in the data
  - Language level: isolated words, sentence, spoken language, read speech, spontaneous speech, dialect ...
  - Speaker level: gender, adult versus child, dialect, age, accent, impaired versus unimpaired (pathological speech), emotion, mood, stress ....
  - Noise
    - Convolutive: recording/transmission condition, reverberation
    - Additive: recording environment, transmission
    - Lombard effect: speaker level variability in noisy environment
- Depending upon the task, a few variabilities are desirable or of interest while others are undesirable or of not interest.

Types of learning

1. Supervised learning
   - Training data is labelled. For example, for a frame of feature vector or a sequence feature vectors we have a "class" label associated to it.
2. Reinforcement learning
   - Training data has partial labels/targets. For example, did a robot carry out the desired action or not?
3. Unsupervised learning
   - Training data does not contain class labels or targets. But, often there is a hidden goal associated with the task. For example, data clustering tasks have a hidden goal such as, minimization of a distance function or maximization of likelihood.

Statistical Pattern Recognition

- Classification
  - Static classification
  - Sequence classification
- Detection: can be regarded as a two class classification problem
- Regression: relation between two variables, namely, measured variable and explanatory variable

Three Key Statistical Rules

1. Bayes's rule:

$$P(A, B) = P(A|B)P(B) = P(B|A)P(A)$$

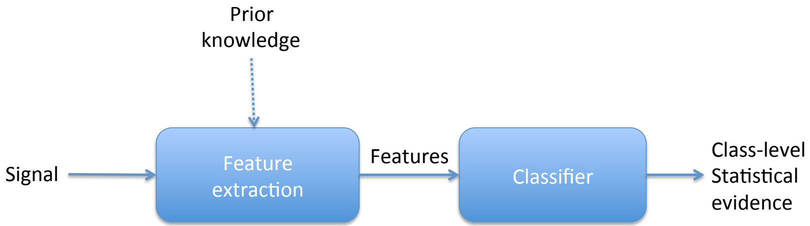
2. If B_k $(k = 1, \ldots, K)$ are mutually exclusive and collectively exhaustive ($\sum_{k=1}^{K} P(B_k) = 1$)

$$P(A) = \sum_{k=1}^{K} P(A, B_k)$$

3. Gibbs sampler:

$$P(B_1, \ldots, B_k, \ldots, B_K) = \prod_{k=1}^{K} P(B_k | B_{k-1}, \ldots, B_1)$$

Static Classification



Speech

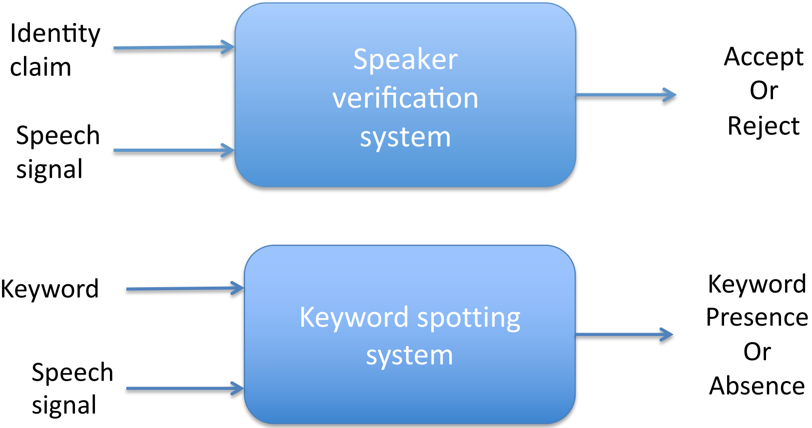
Phoneme
Gender
Speaker
Emotion..

Face image

Person
Age
Gender
Emotion..

Sequence classification

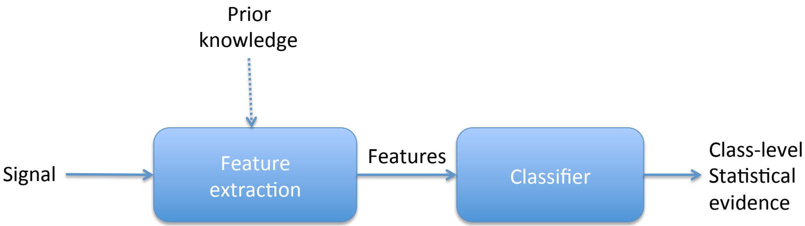
Detection



Hypothesis testing problem

Outline

Static Classification



Speech

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Gender
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Emotion..

Face image

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Theoretical formulation

$$P(C_k|x_m,\Theta) = \frac{p(x_m|C_k,\Theta)\cdot P(C_k|\Theta)}{p(x_m|\Theta)}\ \forall k \in \{1,\cdots K\} \qquad (1)$$

- $P(C_k|x_m,\Theta)$: Posterior probability of class C_k
- $p(x_m|C_k,\Theta)$: Likelihood of class C_k
- $P(C_k|\Theta)$: Prior probability of class C_k
- $p(x_m|\Theta) = \sum_{j=1}^{K} p(x_m|C_j,\Theta)\cdot P(C_j|\Theta)$: Observation likelihood
- Θ: parameters of the statistical model
- $0 \leq P(C_k|x_m,\Theta) \leq 1$ and $\sum_{k=1}^{K} P(C_k|x_m,\Theta) = 1$
- $0 \leq P(C_k|\Theta) \leq 1$ and $\sum_{k=1}^{K} P(C_k|\Theta) = 1$

Generative approach

- Estimate or model $p(x_m|C_k)$ by a probability density function
  - Gaussian or Normal distrution

$$
\begin{aligned}
p(x_m|C_k,\Theta_k) &= N(x_m,\mu_k,\Sigma_k) \\
&= \frac{1}{(2\pi)^{D/2}|\Sigma_k|^{1/2}} \exp\left(-\frac{(x_m-\mu_k)^t\Sigma_k^{-1}(x_m-\mu_k)}{2}\right) \\
\approx & \quad \prod_{d=1}^{D} \frac{1}{\sqrt{2\pi}\sigma_k^d} \exp\left(-\frac{1}{2}\left(\frac{x_m^d-\mu_k^d}{\sigma_k^d}\right)^2\right)
\end{aligned}
$$

  - Gaussian mixture models (GMM)

$$
p(x_m|C_k,\Theta_k) = \sum_{j=1}^{J} c_k^j \cdot N(x_m,\mu_k^j,\Sigma_k^j)
$$

- Estimate prior probability $P(C_k)$ (typically done through counting)
- Apply Eqn. (1)
- Θ: means, variance and Gaussian weights (in the case of GMMs)

EM algorithm for GMMs (1)

$$p(x_m) = \sum_{j=1}^{J} c_j p(x_m|\mu_j, \Sigma_j)$$

with $c_j = P(G_j)$ (Weight fot Gaussian j).

Estimation step:

$$P(G_j|x_m) = \frac{c_j p(x_m|\mu_j^{(t)}, \Sigma_j^{(t)})}{\sum_j c_j p(x_m|\mu_j^{(t)}, \Sigma_j^{(t)})}$$

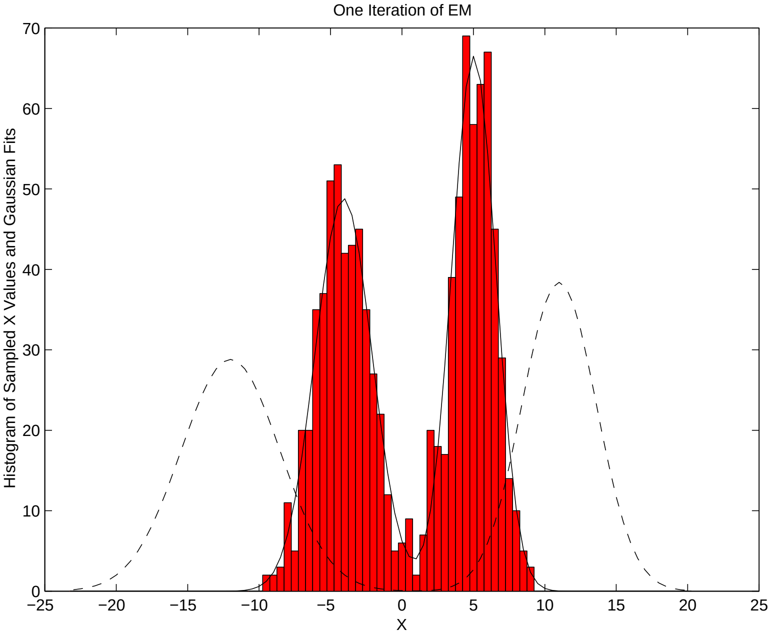
Maximization step:

$$\mu_j^{(t+1)} = \frac{\sum_{m=1}^{n=M} x_m P(G_j|x_m)}{\sum_{m=1}^{m=M} P(G_j|x_m)}$$

$$\Sigma_j^{(t+1)} = \frac{\sum_{m=1}^{m=M} P(G_j|x_m)(x_m - \mu_j^{(t+1)})(x_m - \mu_j^{(t+1)})^T}{\sum_{m=1}^{m=M} P(G_j|x_m)}$$

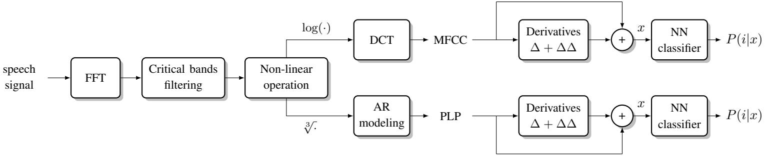
$$c_j^{(t+1)} = \frac{1}{M} \sum_{m=1}^{m=M} P(G_j|x_m)$$

EM algorithm for GMMs (2)



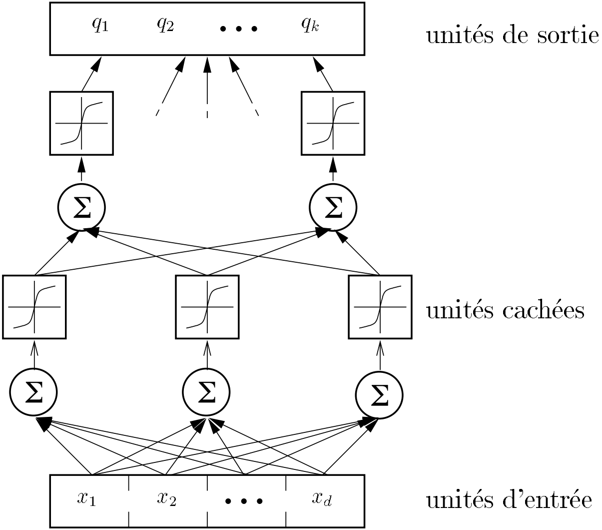
Discriminative approach

- Artificial neural network trained with one hot encoding of target and cross entropy error function (or mean square error function) can directly estimate $P(C_k|x_m, \Theta)$



- Support vector machines (estimation of posterior probability of class not trivial, see Platt's method)
- Θ: parameters of the artificial neural networks (weights and biases) or support vector machines

ANN: Multilayer perceptrons



Typical multilayer perceptron (MLP) architecture, each unit approximating a perceptron.

ANN Training

Supervised training: Input vector sequence:

$$X = \{\mathrm{x}_1, \ldots, \mathrm{x}_n, \ldots, \mathrm{x}_M\}$$

Desired output sequence associated with X:

$$D = \{d(\mathrm{x}_1), \ldots, d(\mathrm{x}_m), \ldots, d(\mathrm{x}_M)\}$$

and $d(\mathrm{x}_m) = (d_1(\mathrm{x}_m), \ldots, d_k(\mathrm{x}_m), \ldots, d_K(\mathrm{x}_m))^{\mathrm{T}}$
In classification mode:

$$d_k(x_m) = \delta_{k\ell} \quad \text{if} \quad \mathrm{x}_m \in C_\ell$$

Parameters Θ: weights and biases

Training Criteria

- Mean Square Error:

$$\underset{\{\Theta\}}{\operatorname{argmin}} \; E = \frac{1}{2} \sum_{m=1}^{M} \sum_{k=1}^{K} \left[g_k(x_m, \Theta) - d_k(x_m) \right]^2$$

- Entropy or relative entropy:

$$\begin{aligned} \underset{\{\Theta\}}{\operatorname{argmin}} \; E_e \quad = \quad & \sum_{m=1}^{M} \sum_{m=1}^{M} \left[d_k(x_m) \log \frac{d_k(x_m)}{g_k(x_m, \Theta)} \right. \\ & \left. + (1 - d_k(x_m) \log \frac{1 - d_k(x_m)}{1 - g_k(x_m, \Theta)} \right] \end{aligned}$$

$g_k(x_m, \Theta)$ denotes the output of the neural network.

Error back propagation training

Minimization of E (or E_e) in the parameter space Θ (weights + biases)

$$\frac{\bigtriangledown E}{\bigtriangledown \Theta} = 0$$

Done via a gradient procedure:

$$\triangle w_{ij} = -\alpha \frac{\partial E}{\partial w_{ij}}$$

α denotes learning rate

Adjust w_{ij} based on $\triangle w_{ij}$.

Offline Error Back-Propagation

Initialize network at random; choose "large" learning rate
Until convergence = true
    For m=1 to M
        Forward computation of $g_k(\mathrm{x}_m, \Theta)$
        Error calculation and global error update
        Error backward propagation
        and compute local $\delta\Theta(\mathrm{x}_m)$
    Θ **update** $= \sum_{m=1}^{M} \delta\Theta(\mathrm{x}_m)$
    If error (on cross-validation set) decreases
        save new parameters
    Otherwise, don't save new parameters
        and decrease learning rate
If learning rate $<$ threshold then convergence = true;

Online Error Back-Propagation

Initialize network at random
Choose "large" learning rate; convergence = false
Until convergence = true
    For m=1 to M (or something else)
        Pick x_m at random
        Forward computation of $g_k(x_m, \Theta)$
        Error calculation
        Error backward propagation and Θ **update**
    If error (on cross-validation set) decreases
        save new parameters
    Otherwise, don't save new parameters
        and decrease learning rate
If learning rate $<$ threshold: convergence = true;

In practice: Mini-batch training, a combination of offline and online error back propagation.

Cross-validation training (1)

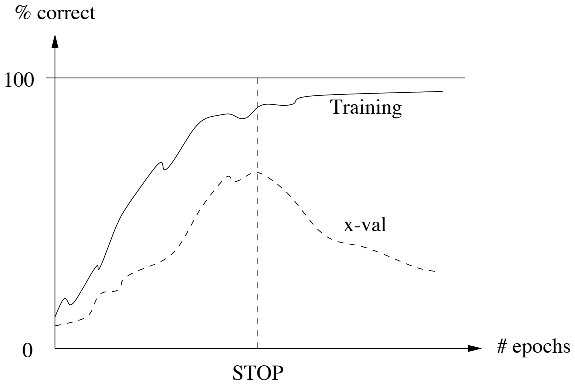
After each MLP training epoch:

1. check recognition performance on independent data set
2. stop training if rec performance starts to decrease and learning rate below a given threshold

Remarks: there are other solutions like

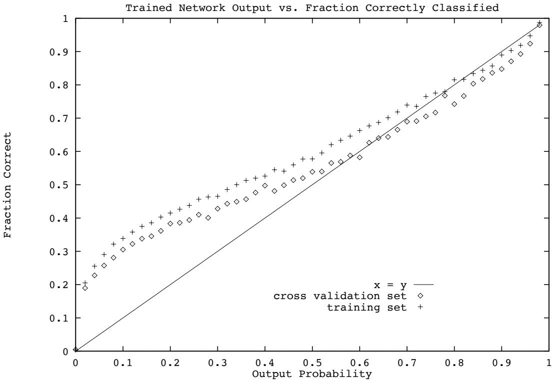
- Forcing small weights
- "Optimal Brain Damage"
- Regularized training (Bayesian approach)

Cross-validation training (2)



Example of crossvalidation training. x-val represents the crossvalidation data on which classification performance is regularly checked. Training is stopped when performance on x-val data reaches the maximum.

Interpretation of ANN output $g_k(\mathrm{x}_m, \Theta)$



ANN output $g_k(\mathrm{x}_m, \Theta)$ is an estimate of posterior probability of class C_k, i.e. $P(C_k|\mathrm{x}_m)$.

Decision making

- Maximum likelihood

$$C^*_{mle} = \arg\max_k p(X|C_k, \Theta)$$

$$p(X|C_k, \Theta) = \prod_{m=1}^{M} P(x_m|C_k, \Theta) \text{(Assuming i.i.d)}$$

- Maximum aposteriori probability

$$C^*_{map} = \arg\max_k p(C_k|X, \Theta)$$

$$P(C_k|X, \Theta) = \frac{1}{Z} \cdot \prod_{m=1}^{M} P(C_k|x_m, \Theta) \text{(Assuming i.i.d)}$$

or

$$P(C_k|X, \Theta) = \frac{1}{Z} \cdot \sum_{m=1}^{M} P(C_k|x_m, \Theta)$$

Z is a normalization factor.

Better to perform computation using logarithm to avoid underflow issues.

Outline

Sequence classification

Statistical ASR

Given feature observation $X = \{x_1, \cdots x_m, \cdots x_M\}$ predict the most probable word sequence $W^* = \{w_1^* \cdots w_n^* \cdots w_N^*\}$

$$
\begin{aligned}
W^* &= \arg\max_{W_i \in \mathcal{W}} P(W_i | X, \Theta) \\
&= \arg\max_{W_i \in \mathcal{W}} \frac{p(X|W_i, \Theta_a) \cdot P(W_i|\Theta_l)}{p(X|\Theta)} \\
&= \arg\max_{W_i \in \mathcal{W}} p(X|W_i, \Theta_a) \cdot P(W_i|\Theta_l),
\end{aligned}
$$

where W_i denotes a word hypothesis, $\mathcal{W}$ denotes a set of word hypotheses and $\Theta = \{\Theta_a, \Theta_l\}$

- Acoustic modeling: estimation of $p(X|W_i, \Theta_a)$ using hidden Markov models (HMMs)
- Language modeling: estimation of $P(W_i|\Theta_l)$ using discrete Markov models (DMMs)

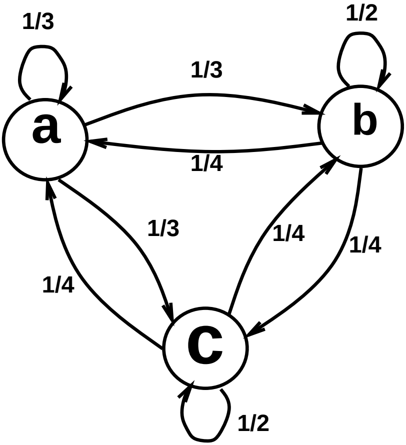
Discrete Markov Model (DMM)

- Stochastic finite state automaton
- *MM* built up from states q_ℓ from a set of classes (states) $\Omega = \{\omega_1, \ldots, \omega_k, \ldots, \omega_K\}$
- q^n particular state of M visited at time n,
- $q_\ell^n \; \equiv \; \{q^n = q_\ell\}$, $q_l \in \Omega$
- *MM* is defined by topology, i.e., how the states are connected
  See HMM lab exercise 1
- Parametrized by:

$$\begin{aligned} P(q_\ell^n | q_k^{n-1}, q_j^{n-2}, \ldots) &\simeq P(q_\ell^n | q_k^{n-1}) \quad (\textit{1st order Markov}) \\ &\simeq P(q_\ell | q_k) = P_{k\ell} \quad (\textit{time independent}) \end{aligned}$$

Note: $q_l, q_k \in \Omega$
Transition probability matrix: $A = \{P_{k,\ell}\}$.

DMM (2)



Example of fully connected discrete Markov model with $\Omega = \{a, b, c\}$. For example, in case of weather model: "a" = "cloudy", "b"= "rainy" and "c" = "sunny"

Typical Problems (1)

- **Probability of a particular path**

$$P(Q|MM) = P(q^1|q_i^0)P(q^2|q^1)\dots P(q^n|q^{n-1})\dots P(q^N|q^{N-1}) = \prod_{n=1}^{N} P(q^n|q^{n-1})$$

One way to estimate $P(W_i|\Theta_l)$, e.g.

$$P(W^*|\Theta_l) = \prod_{n=1}^{N} P(w_n^*|w_{n-1}^*)$$

- **State duration distribution**

Probability to stay in state q_i for *exactly* d time steps?

$$Q = \{q_i^0, q_i^1, q_i^2, \dots, q_i^d, q_j^{d+1}\}, \text{ with } j \neq i$$

and:

$$P(Q|MM) = (P_{ii})^{d-1}(1 - P_{ii})$$

See HMM lab exercise 1

Typical Problems (2)

- **Probability to go from state q_i to q_j in N steps**

$$P(q_j^N|q_i^0) = \sum_{n=0}^{N} \sum_{\ell=1}^{L} P(q_j^N, q_\ell^n|q_i^0)$$

Defining

$$\alpha(\ell, n) = P(q_\ell^n|q_i^0, N)$$

We have:

$$\alpha(\ell, n+1) = \sum_k \alpha(k, n) P_{k\ell}$$

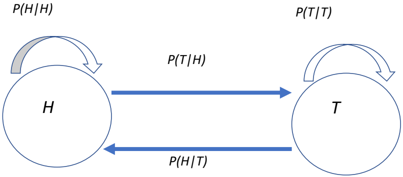
$$P(q_j^N|q_i^0) = \alpha(j, N)$$

Typical Problems (3)

- **Probability of best path of length N between q_i and q_j**
  If $\overline{P}(k,n)$ is probability of best path to go from q_i to q_k in n steps:
  $$\overline{P}(\ell, n+1) = \max_k \overline{P}(k,n) P_{k\ell}$$
  and
  $$\overline{P}(q_j^N | q_i^0) = P(j, N)$$
  Generalization:
  $$A^n(i,j) = P(q_j^n | q_i^0)$$

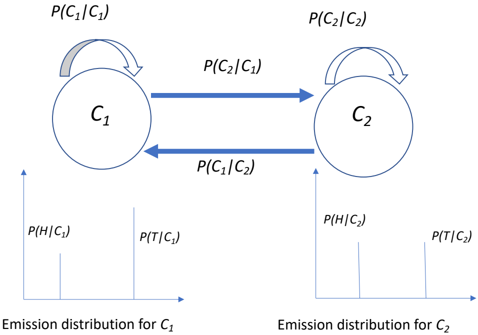
From DMM to HMM (1)

- Coin tossing and only the results of each coin toss i.e. Heads (H) or Tails (T) is revealed
  $H\ H\ T\ T\ T\ H\ H\ H\ H\ T\ T\ldots$
- 1-coin model: DMM with two states $\Omega = \{H, T\}$ and all transition probabilities are equal to 0.5.



From DMM to HMM (2)

- 2-coin model: HMM with two states $\Omega = \{C_1, C_2\}$; each state associated with $P(H|C_i)$ and $P(T|C_i)$ $i \in \{1, 2\}$; and the transition probability reflects the probability of choosing one of the (possibly biased) coins



Estimation of $P(X|W_i, \Theta_a)$ using HMMs

$$
\begin{aligned}
P(X|W_i, \Theta_a) &= \sum_{Q \in W_i} P(X, Q|W_i, \Theta_a) \\
&= \sum_{Q \in W_i} P(X|Q, W_i) P(Q|W_i),
\end{aligned}
$$

where $Q = \{q_1, \cdots q_m, \cdots q_M\}$ denotes sequence of HMM states.
After i.i.d and first order Markov assumption

$$
\begin{aligned}
P(X|W_i, \Theta_a) &= \sum_{Q \in W_i} \prod_{m=1}^{M} p(x_m|q_m) \prod_{m=1}^{M} P(q_m|q_{m-1}) \\
&= \sum_{Q \in W_i} \prod_{m=1}^{M} p(x_m|q_m) P(q_m|q_{m-1}) \text{ Full likelihood} \\
&\approx \max_{Q \in W_i} \prod_{m=1}^{M} p(x_m|q_m) P(q_m|q_{m-1}) \text{ Viterbi approx.}
\end{aligned}
$$

For the sake of simplicity, Θ_a and W_i are dropped in the latter equations.
$p(x_m|q_m)$ is referred to as emission likelihood and $P(q_m|q_{m-1})$ state transition probabilities. *See HMM lab exercises 3 and 4.*

Estimation of emission likelihood

- Gaussians and Gaussian-Mixtures

$$p(x_m|q_m = k, \Theta_a) = N(x_m, \mu_k, \Sigma_k)$$
$$= \frac{1}{(2\pi)^{D/2}|\Sigma_k|^{1/2}} \exp\left(-\frac{(x_m - \mu_k)^t \Sigma_k^{-1}(x_m - \mu_k)}{2}\right)$$

OR :

$$p(x_m|q_m = k, \Theta_a) = \sum_{j=1}^{J} c_k^j N(x_m, \mu_k^j, \Sigma_k^j)$$

- Artificial neural networks: estimate scaled-likelihood $p_{sl}(x_m|q_m = k, \Theta_a)$

$$p_{sl}(x_m|q_m = k, \Theta_a) = \frac{p(x_m|q_m = k, \Theta_a)}{p(x_m|\Theta_a)} = \frac{P(q_m = k|x_m, \Theta_a)}{P(q_m = k|\Theta_a)}$$

Outline

Detection

$$\frac{p(X|\text{genuine speaker})}{p(X|\text{impostor})} \geq \delta_{asv}$$

Challenge: modeling or estimation of $p(X|\text{impostor})$

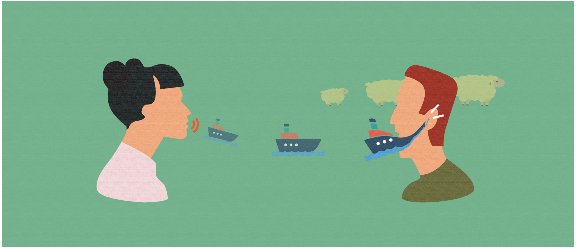
$$\frac{p(X|\text{keyword})}{p(X|\text{not keyword})} \geq \delta_{kws}$$

Challenge: modeling or estimation of $p(X|\text{not keyword})$

Two types of error: False negative, False positive

Outline

Paralinguistics



States and traits manifested in speech communication

- long-term: age, gender, accent, personality ...
- medium-term: mood, sleepiness, intoxication, social role ...
- short-term: emotion, voice quality ...
- speech and language pathologies

Paralinguistics $\propto$ speech, language, physiology, sociology, psychology, health ....

Paralinguistics

Recent examples from workshops within the community:
Interspeech Computational Paralinguistics Challenge [1]
ACM Audio/Visual Emotion Challenge Workshop [2]

- Styrian dialects: northern, urban, eastern
- native language: 11 languages (ger, fra, ita, spa, hin)
- Degree of nativeness: 0 (no foreign accent) ... 6 (strong foreign accent)
- emotions: anger, empathic, neutral, positive, rest
- alcohol intoxication: no/yes
- Parkinson's disease: intelligibility 0 - 100
- sleepiness: 1 - 9
- Alzheimer's disease: no/yes

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[1] http://www.compare.openaudio.eu/
[2] https://sites.google.com/view/avec2019

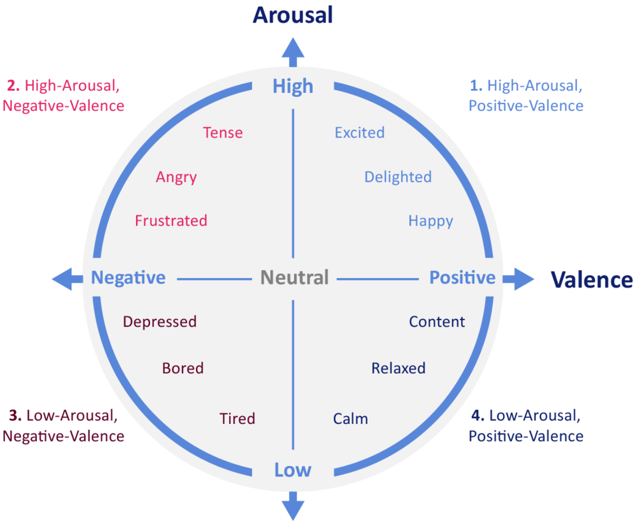
Example application areas

Challenges in Paralinguistics (1)

Data Labeling

- Establishing a ground-truth is not a trivial task
  $\rightarrow$ labels can be based on other fields
- humans are typically used to label/rate the data
  $\rightarrow$ how to select human raters?
- human ratings can differ
  $\rightarrow$ need to measure inter-rater agreement: see Cohen's kappa
- labels are typically assigned to a whole utterance or recording
  (may refer to only some part of recording)

Emotion class labels



Sleepiness rating

Rating	Verbal descriptions
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert, fighting sleep

also see: Likert scale

Challenges in Paralinguistics (2)

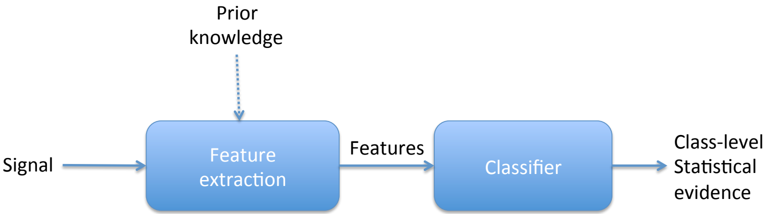
Features

- which features are relevant?
- relevant information is present at short-term (segmental) level or/and long-term (supra-segmental) level?
- how to use prior knowledge or feature selection?
- how to obtain short-term or long-term representations?

Challenges in Paralinguistics (3)

- Data scarcity
  - Collecting large data sets is not an easy task
    - simulated versus real e.g., acted emotion versus real emotion
    - ethical restrictions e.g. in the case of health care
    - privacy issues
    - ...
  - transfer learning from resource-rich task (e.g. with deep learning)
  - data augmentation - risk of obliterating important information
- Cross-database, cross-lingual and cross-cultural generalisation is not trivial.

Pattern recognition



Speech

Phoneme
Gender
Speaker
Emotion..

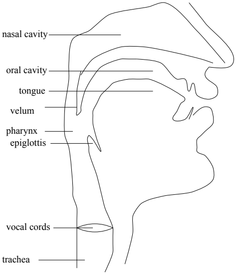
Face image

Person
Age
Gender
Emotion..

Speech Analysis

Various aspects of speech production and perception:

- Respiration
  - pause patterns, speech rate, loudness through excitation strength
- Phonation
  - analysis of pitch (jitter and shimmer)
- Articulation - changes in vocal tract shape
  - use source-system decomposition
  - analysis of voiced speech (vowel formants)



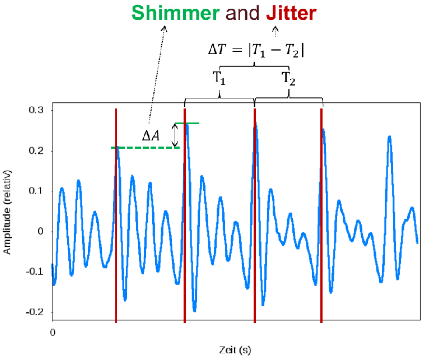
Respiration and pause patterns

- pitch
- loudness
- statistics of silent regions
- statistics of unvoiced regions per second (pseudo-rate)

Phonation and voice-quality features

Measuring irregular phonation

- Jitter: deviations of pitch from perfect periodicity
- Shimmer: deviation of energy of signal



- Harmonics-to-Noise Ratio (HNR):
  $HNR = 10 * \log \frac{ACF[T0]}{ACF[0] - ACF[T0]}$
  ACF denotes autocorrelation function and T_0 denotes pitch period.

Articulation features

Measuring vocal tract shaping

- Mel Frequency Cepstral Coefficients (MFCCs)
- Perceptual Linear Prediction Coefficients (PLPs)
- Vowel formant frequencies
- Spectral slopes and ratios
- ...

Feature sets

Traditional approach to paralinguistic problems:
Use large quantities of short-time acoustic features

Several version of feature sets, easily extractable with openSMILE [3]

- openSMILE feature set: 6773 LLDS and functionals
- eGeMAPS feature set: 88 LLDS

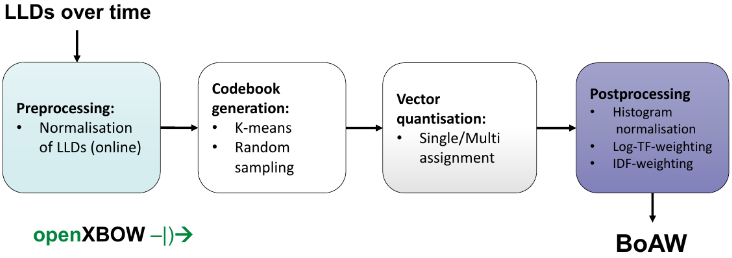
How to classify frame-level acoustic features?

1. Majority vote of frame-level feature vectors
2. Summarize frame-level feature vectors into per-utterance vectors

[3] https://www.audeering.com/opensmile/

Per-utterance representations

- acoustic features are summarized in statistical functionals (e.g. means, moments, extrema, percentile, slopes, regression lines, max, min)
- bag-of-audio–word (BoAW) representations derived from bag-of-word vectors used in NLP [4]



- robust, time-invariant, non-reconstructable (good for privacy)

[4] https://github.com/openXBOW/openXBOW

Classification

Choice of classifier is dictated by amount of data available

- k-Nearest Neighbors (kNN)
  - works well with small data sets
- Support Vector Machine (SVM)
  - works well with small data sets and high dimensions
- Random forest
  - works well with small data sets and high dimensions
- Boosting
  - works well with small data sets and high dimensions
- Neural Networks (NN)
  - May not suit well for small data sets

In some problems, classification is replaced by regression.

Evaluation

Common evaluation metrics:

- Regression
  - Pearson's correlation r: linear correlation coefficient
  - Spearman's cross-correlation ρ: non-parametric correlation coefficient
- Classification
  - Unweighted Average Recall (UAR): consider performance across non-balanced class distributions

Common evaluation schemes

- N-fold cross-validation
- leave-one-speaker-out cross-validation

Thank you for your attention!

Dr. Mathew Magimai Doss

Idiap Research Institute, Martigny, Switzerland