Lecture 7

LVCSR Training and Decoding (Part A)

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Lab 2
- Handed back this lecture or next.

Lab 3 extension
- Due nine days from now (Friday, Mar. 18) at 6pm.

Visit to IBM Watson Astor Place
- April 1, 11am. (About 1h?)

Spring recess next week; no lecture.
Feedback

- Clear (9)
- Pace: fast (1)
- Muddiest: context models (3); diagonal GMM splitting (2); arcs v. state probs (1)

Comments (2+ votes):
- Nice song (4)
- Hard to see chalk on blackboard (3)
- Lab 3 better than Lab 2 (2)
- Miss Michael on right (1); prefer Michael on left (1)
The Big Picture

- **Weeks 1–4**: Signal Processing, Small vocabulary ASR.
- **Weeks 5–8**: Large vocabulary ASR.
  - **Week 5**: Language modeling (for large vocabularies).
  - **Week 6**: Pronunciation modeling — acoustic modeling for large vocabularies.
  - **Week 7, 8**: Training, decoding for large vocabularies.
- **Weeks 9–13**: Advanced topics.
Outline

- Part I: The LVCSR acoustic model.
- Part II: Acoustic model training for LVCSR.
- Part III: Decoding for LVCSR (inefficient).
  - Part IV: Introduction to finite-state transducers.
- Part V: Search (Lecture 8).
  - Making decoding for LVCSR efficient.
Part I

The LVCSR Acoustic Model
What is LVCSR?

Demo from https://speech-to-text-demo.mybluemix.net/
What is LVCSR?

- Large vocabulary Continuous Speech Recognition.
  - Phone-based modeling vs. word-based modeling.
- Continuous.
  - No pauses between words.
How do you evaluate such an LVCSR system?

<table>
<thead>
<tr>
<th>Ground Truth</th>
<th>Hello how can I help you today</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASR</td>
<td>Hello ___ can EYE help you TO today</td>
</tr>
</tbody>
</table>

**WER**

\[
WER = \frac{\#Ins + \#Sub + \#Del}{\#Words}
\]
What do we have to begin training an LVCSR system?

- Audio Recording 1
- Audio Recording 2
- Transcript 1
- Transcript 2

Parallel database of audio and transcript

Lexicon or dictionary
The Fundamental Equation of ASR

\[ w^* = \arg \max_{\omega} P(\omega | x) \]  
\[ = \arg \max_{\omega} \frac{P(\omega)P(x|\omega)}{P(x)} \]  
\[ = \arg \max_{\omega} P(\omega)P(x|\omega) \]

- \( w^* \) — best sequence of words (class)
- \( x \) — sequence of acoustic vectors
- \( P(x|\omega) \) — acoustic model.
- \( P(\omega) \) — language model.
\[ P_\omega(x) = \sum_A P_\omega(x, A) = \sum_A P_\omega(A) \times P_\omega(x|A) \]  (4)

\[ \approx \max_A P_\omega(A) \times P_\omega(x|A) \]  (5)

\[ = \max_A \prod_{t=1}^T P(a_t) \prod_{t=1}^T P(\vec{x}_t|a_t) \]  (6)

\[ \log P_\omega(x) = \max_A \left[ \sum_{t=1}^T \log P(a_t) + \sum_{t=1}^T \log P(\vec{x}_t|a_t) \right] \]  (7)

\[ P(\vec{x}_t|a_t) = \sum_{m=1}^M \lambda_{a_t,m} \prod_{\text{dim } d} \mathcal{N}(X_{t,d}; \mu_{a_t,m,d}, \sigma_{a_t,m,d}) \]  (8)
The Acoustic Model: Large Vocabulary

\[
P_\omega(x) = \sum_A P_\omega(x, A) = \sum_A P_\omega(A) \times P_\omega(x|A) \quad (9)
\]

\[
\approx \max_A P_\omega(A) \times P_\omega(x|A) \quad (10)
\]

\[
= \max_A \prod_{t=1}^T P(a_t) \prod_{t=1}^T P(\tilde{x}_t|a_t) \quad (11)
\]

\[
\log P_\omega(x) = \max_A \left[ \sum_{t=1}^T \log P(a_t) + \sum_{t=1}^T \log P(\tilde{x}_t|a_t) \right] \quad (12)
\]

\[
P(\tilde{x}_t|a_t) = \sum_{m=1}^M \lambda_{at,m} \prod_{d=1}^D \mathcal{N}(X_{t,d}; \mu_{at,m,d}, \sigma_{at,m,d}) \quad (13)
\]
What Has Changed?

- The HMM.
  - Each alignment $A$ describes a path through an HMM.
- Its parameterization.
  - In $P(\vec{x}_t | a_t)$, how many GMM’s to use? (Share between HMM’s?)
Describing the Underlying HMM

Fundamental concept: how to map a word (or baseform) sequence to its HMM.

- In training, map reference transcript to its HMM.
- In decoding, glue together HMM’s for all allowable word sequences.
One HMM per word.

Glue together HMM for each word in word sequence.
The HMM: Large Vocabulary

- One HMM per phone.
- Glue together HMM for each phone in phone sequence.
  - Map word sequence to phone sequence using baseform dictionary.
    - The rain in Spain falls . . .
An Example: Word to HMM

acapulco  AE K AX P AH L K OW
acapulco  AA K AX P UH K OW
An Example: Words to HMMs

HMM phone models

 Lexicon

Sentence model: 'he is new'
A set of arcs in a Markov model are tied to one another if they are constrained to have identical output distributions.
Now, in this example . . .

- The rain in Spain falls . . .

```
<table>
<thead>
<tr>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>yes</td>
</tr>
</tbody>
</table>

Is phone 2 positions to the left a vowel

- no
- {P EY N}, {R, EY, N}, {IX N}

Is phone 1 position to the left a long vowel

- yes
- no
- {IX N}

Is phone 1 position to the left a boundary phone

- no
- yes
- {P EY N}, {R, EY, N}

Is phone 2 positions to the left a plosive

- yes
- no
- {R, EY, N}
- {P EY N}
```
I Still Don’t See What’s Changed

- HMM **topology** typically doesn’t change.
- HMM **parameterization** changes.
Parameterization

- Small vocabulary.
  - One GMM per state (three states per phone).
  - No sharing between phones in different words.

- Large vocabulary, context-independent (CI).
  - One GMM per state.
  - *Tying* between phones in different words.

- Large vocabulary, context-dependent (CD).
  - Many GMM’s per state; GMM to use depends on phonetic context.
  - Tying between phones in different words.
Context-Dependent Parameterization

- Each phone HMM state has its own decision tree.
  - Decision tree asks questions about phonetic context. (Why?)
  - One GMM per leaf in the tree. (Up to 200+ leaves/tree.)
- How will tree for first state of a phone tend to differ . . .
  - From tree for last state of a phone?
- Terminology.
  - *triphone* model — ±1 phones of context.
  - *quinphone* model — ±2 phones of context.
Example of Tying

- Examples of “0” will affect models for “3” and “4”
- Useful in large vocabulary systems (why?)
A Real-Life Tree

In practice:

- These trees are built on one-third of a phone, i.e., the three states of the HMM for a phone correspond to the beginning, middle and end of a phone.
- Context-independent versions
- Context-dependent versions
Another Sample Tree

```
AA-b-0
[-2=Voice]  
No  Yes

AA-b-2  AA-b-1
[-1=SIL]  

No  Yes

...  GMM AA-b-0

...  ...
```
Pop Quiz

- System description:
  - 1000 words in lexicon; average word length = 5 phones.
  - There are 50 phones; each phone HMM has three states.
  - Each decision tree contains 100 leaves on average.

- How many GMM’s are there in:
  - A small vocabulary system (word models)?
  - A CI large vocabulary system?
  - A CD large vocabulary system?
Context-Dependent Phone Models

- Typical model sizes:

<table>
<thead>
<tr>
<th>type</th>
<th>HMM</th>
<th>GMM’s/ state</th>
<th>GMM’s</th>
<th>Gaussians</th>
</tr>
</thead>
<tbody>
<tr>
<td>word</td>
<td>per word</td>
<td>1</td>
<td>10–500</td>
<td>100–10k</td>
</tr>
<tr>
<td>CI phone</td>
<td>per phone</td>
<td>1</td>
<td>~150</td>
<td>1k–3k</td>
</tr>
<tr>
<td>CD phone</td>
<td>per phone</td>
<td>1–200</td>
<td>1k–10k</td>
<td>10k–300k</td>
</tr>
</tbody>
</table>

- 39-dimensional feature vectors ⇒ ~80 parameters/Gaussian.

- Big models can have tens of millions of parameters.
Given a word sequence, you should understand how to . . .

- Layout the corresponding HMM topology.
- Determine which GMM to use at each state, for CI and CD models.
What About Transition Probabilities?

- This slide only included for completeness.
- Small vocabulary.
  - One set of transition probabilities per state.
  - No sharing between phones in different words.
- Large vocabulary.
  - One set of transition probabilities per state.
  - Sharing between phones in different words.
- What about context-dependent transition modeling?
Recap

Main difference between small vocabulary and large vocabulary:

- Allocation of GMM’s.
- Sharing GMM’s between words: needs less GMM’s.
- Modeling context-dependence: needs more GMM’s.
- Hybrid allocation is possible.

Training and decoding for LVCSR.

- In theory, any reason why small vocabulary techniques won’t work?
- In practice, yikes!
Points to Ponder

- Why deterministic mapping?
  - DID YOU $\Rightarrow$ D IH D JH UW
  - The area of *pronunciation modeling*.

- Why decision trees?
  - Unsupervised clustering.
Acoustic Model Training for LVCSR
Phase 1: Collect underpants.
  - Initialize all Gaussian means to 0, variances to 1.
Phase 2: Iterate over training data.
  - For each word, train associated word HMM . . .
  - On all samples of that word in the training data . . .
  - Using the Forward-Backward algorithm.
Phase 3: Profit!
Large Vocabulary Training

- What’s changed going to LVCSR?
  - Same HMM topology; just more Gaussians and GMM’s.
- Can we just use the same training algorithm as before?
Where Are We?

1. The Local Minima Problem
2. Training GMM’s
3. Building Phonetic Decision Trees
4. Details
5. The Final Recipe
Flat or Random Start

- Why does this work for small models?
  - We believe there’s a huge global minimum . . .
  - In the “middle” of the parameter search space.
  - With a neutral starting point, we’re apt to fall into it.
  - (Who knows if this is actually true.)

- Why doesn’t this work for large models?
Training a Mixture of Two 2-D Gaussians

- Flat start?
  - Initialize mean of each Gaussian to 0, variance to 1.
Training a Mixture of Two 2-D Gaussians

- Random seeding?
  - Picked 8 random starting points ⇒ 3 different optima.
Training Hidden Models

- (MLE) training of models with hidden variables has local minima.
- What are the hidden variables in ASR?
  - i.e., what variables are in our model ... 
  - That are not observed.
How To Spot Hidden Variables

\[ P_\omega(x) = \sum_A P_\omega(x, A) = \sum_A P_\omega(A) \times P_\omega(x|A) \quad (14) \]

\[ \approx \max_A P_\omega(A) \times P_\omega(x|A) \quad (15) \]

\[ = \max_A \prod_{t=1}^T P(a_t) \prod_{t=1}^T P(\vec{x}_t|a_t) \quad (16) \]

\[ \log P_\omega(x) = \max_A \left[ \sum_{t=1}^T \log P(a_t) + \sum_{t=1}^T \log P(\vec{x}_t|a_t) \right] \quad (17) \]

\[ P(\vec{x}_t|a_t) = \sum_{m=1}^M \lambda_{a_t,m} \prod_{\text{dim } d} N(\vec{x}_{t,d}; \mu_{a_t,m,d}, \sigma_{a_t,m,d}) \quad (18) \]
Gradient Descent and Local Minima

- EM training does hill-climbing/gradient descent.
- Finds “nearest” optimum to where you started.
What To Do?

- Insight: If we know the “correct” hidden values for a model:
  - *e.g.*, which arc and which Gaussian for each frame . . .
  - Training is easy! (No local minima.)
  - Remember Viterbi training given fixed alignment in Lab 2.
- Is there a way to guess the correct hidden values for a large model?
Recall that all of our acoustic models, from simple to complex:

- Generally use the same HMM topology!
- (All that differs is how we assign GMM’s to each arc.)

Given an alignment (from arc/phone states to frames) for simple model . . .

- It is straightforward to compute analogous alignment for complex model!
Recipe:

- Start with model simple enough that flat start works.
- Iteratively build more and more complex models . . .
- By using last model to seed hidden values for next.

Need to come up with sequence of successively more complex models . . .

- With related hidden structure.
How To Seed Next Model From Last

- Directly via hidden values, *e.g.*, alignment.
  - *e.g.*, *single-pass retraining*.
  - Can be used between very different models.

- Via parameters.
  - Seed parameters in complex model so that . . .
  - Initially, will yield same/similar alignment as in simple model.
  - *e.g.*, moving from CI to CD GMM’s.
Recurring motif in acoustic model training.
The reason why state-of-the-art systems . . .
  Require many, many training passes, as you will see.
Recipes handed down through the generations.
  Discovered via sweat and tears.
  Art, not science.
  But no one believes these find global optima . . .
  Even for small problems.
Overview of Training Process

- Build CI single Gaussian model from flat start.
- Use CI single Gaussian model to seed CI GMM model.
- Build phonetic decision tree (using CI GMM model to help).
- Use CI GMM model to seed CD GMM model.
Where Are We?

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Case Study: Training a GMM

- Recursive mixture splitting.
  - A sequence of successively more complex models.
  - Perturb means in opposite directions; same variance;
    Train.
  - (Discard Gaussians with insufficient counts.)
- $k$-means clustering.
  - Seed means in one shot.
Mixture Splitting Example

- Split each Gaussian in two ($\pm 0.2 \times \bar{\sigma}$)
Applying Mixture Splitting in ASR

Recipe:
- Start with model with 1-component GMM’s (à la Lab 2).
- Split Gaussians in each output distribution simultaneously.
- Do many iterations of FB.
- Repeat.

Real-life numbers:
- Five splits spread within 30 iterations of FB.
Another Way: Automatic Clustering

- Use unsupervised clustering algorithm to find clusters 
  \((k\text{-Means Clustering})\)
- Given clusters . . .
  - Use cluster centers to seed Gaussian means.
  - FB training.
  - (Discard Gaussians with insufficient counts.)
**k-Means Clustering**

- Select desired number of clusters \( k \).
- Choose \( k \) data points randomly.
  - Use these as initial cluster centers.
- “Assign” each data point to nearest cluster center.
- Recompute each cluster center as . . .
  - Mean of data points “assigned” to it.
- Repeat until convergence.
$k$-Means Example

- Pick random cluster centers; assign points to nearest center.
Use centers as means of Gaussians; train, yep.
The Final Mixtures, Splitting vs. k-Means
Technical Aside: \( k \)-Means Clustering

- When using Euclidean distance . . .
- \( k \)-means clustering is equivalent to . . .
  - Seeding Gaussian means with the \( k \) initial centers.
  - Doing Viterbi EM update, keeping variances constant.
To train each GMM, use \( k \)-means clustering . . .
- On what data? Which frames?
- Huh?
  - How to decide which frames align to each GMM?
- This issue is evaded for mixture splitting.
  - Can we avoid it here?
Forced Alignment

- Viterbi algorithm.
  - Finds most likely alignment of HMM to data.

Need existing model to create alignment. (Which?)
Recap

- You can use single Gaussian models to seed GMM models.
  - Mixture splitting: use $c$-component GMM to seed $2c$-component GMM.
  - $k$-means: use single Gaussian model to find alignment.
- Both of these techniques work about the same.
  - Nowadays, we primarily use mixture splitting.
Where Are We?

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What Do We Need?

- For each tree/phone state . . .
  - List of frames/feature vectors associated with that tree.
  - (This is the data we are optimizing the likelihood of.)
  - For each frame, the phonetic context.
- A list of candidate questions about the phonetic context.
  - Ask about phonetic concepts; e.g., vowel or consonant?
  - Expressed as list of phones in set.
  - Allow same questions to be asked about each phone position.
  - Handed down through the generations.
Training Data for Decision Trees

- Forced alignment/Viterbi decoding!
- Where do we get the model to align with?
  - Use CI phone model or other pre-existing model.

<table>
<thead>
<tr>
<th>frame</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>…</th>
</tr>
</thead>
<tbody>
<tr>
<td>arc</td>
<td>DH₁</td>
<td>DH₂</td>
<td>AH₁</td>
<td>AH₂</td>
<td>D₁</td>
<td>D₁</td>
<td>D₂</td>
<td>D₂</td>
<td>D₂</td>
<td>AO₁</td>
<td>…</td>
</tr>
</tbody>
</table>
Building the Tree

- A set of events \( \{(\vec{x}_i, p_L, p_R)\} \) (possibly subsampled).
- Given current tree:
  - Choose question of the form . . .
  - “Does the phone in position \( j \) belong to the set \( q \)?” . . .
  - That optimizes \( \prod_i P(\vec{x}_i|\text{leaf}(p_L, p_R)) \) . . .
  - Where we model each leaf using a single Gaussian.
- Can efficiently build whole level of tree in single pass.
- See Lecture 6 slides and readings for the gory details.
Seeding the Context-Dependent GMM’s

- Context-independent GMM’s: one GMM per phone state.
- Context-dependent GMM’s: \( l \) GMM’s per phone state.
- How to seed context-dependent GMM’s?
  - *e.g.*, so that initial alignment matches CI alignment?
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Where Are We?

Details

- Maximum Likelihood Training?
- Viterbi vs. Non-Viterbi Training
- Graph Building
The Original Story, Small Vocabulary

- One HMM for each word; flat start.
- Collect all examples of each word.
  - Run FB on those examples to do maximum likelihood training of that HMM.
The New Story

- One HMM for each word *sequence*!?  
  - But tie parameters across HMM’s!
- Do complex multi-phase training.
- Are we still doing anything resembling *maximum likelihood* training?
Maximum Likelihood Training?

- Regular training iterations (FB, Viterbi EM).
  - Increase (Viterbi) likelihood of data.
- Seeding last model from next model.
  - Mixture splitting.
  - CI $\Rightarrow$ CD models.
- (Decision-tree building.)
Maximum Likelihood Training?

- Just as LM’s need to be smoothed or regularized.
  - So do acoustic models.
  - Prevent extreme likelihood values (e.g., 0 or $\infty$).
- ML training maximizes training data likelihood.
  - We actually want to optimize test data likelihood.
  - Let’s call the difference the overfitting penalty.
- The overfitting penalty tends to increase as . . .
  - The number of parameters increase and/or . . .
  - Parameter magnitudes increase.
Regularization/Capacity Control

- Limit size of model.
  - Will training likelihood continue to increase as model grows?
  - Limit components per GMM.
  - Limit number of leaves in decision tree, i.e., number of GMM’s.
- Variance flooring.
  - Don’t let variances go to 0 ⇒ infinite likelihood.
Details

- Maximum Likelihood Training?
- Viterbi vs. Non-Viterbi Training
- Graph Building
Two Types of Updates

- “Full” EM.
  - Compute true posterior of each hidden configuration.
- Viterbi EM.
  - Use Viterbi algorithm to find most likely hidden configuration.
  - Assign posterior of 1 to this configuration.
- Both are valid updates; instances of generalized EM.
Examples

- Training GMM’s.
  - Mixture splitting vs. $k$-means clustering.
- Training HMM’s.
  - Forward-backward vs. Viterbi EM (Lab 2).
- Everywhere you do a forced alignment.
  - Refining the reference transcript.
  - What is non-Viterbi version of decision-tree building?
When To Use One or the Other?

- Which version is more expensive computationally?
  - Optimization: need not realign every iteration.
- Which version finds better minima?
- If posteriors are very sharp, they do almost the same thing.
  - Remember example posteriors in Lab 2?
- Rule of thumb:
  - When you’re first training a “new” model, use full EM.
  - Once you’re “locked in” to an optimum, Viterbi is fine.
Where Are We?

Details

- Maximum Likelihood Training?
- Viterbi vs. Non-Viterbi Training
- Graph Building
Building HMM’s For Training

- When doing Forward-Backward on an utterance . . .
  - We need the HMM corresponding to the reference transcript.
- Can we use the same techniques as for small vocabularies?
Word Models

- Reference transcript

- Replace each word with its HMM
Context-Independent Phone Models

- **Reference transcript**

  ![Diagram of THE and DOG with arrows indicating pronunciation]

- **Pronunciation dictionary.**
  - Maps each word to a sequence of phonemes.

  ![Diagram showing pronunciation of THE with associated phonemes]

- **Replace each phone with its HMM**

  ![Diagram showing HMMs for DH, AH, D, AH, D, AO, and G]
Need pronunciation of every word in training data.
  Including pronunciation variants
  THE(01) DH AH
  THE(02) DH IY

Listen to data?
Use automatic spelling-to-sound models?
Why not consider multiple baseforms/word for word models?
But Wait, It’s More Complicated Than That!

- Reference transcripts are created by humans . . .
  - Who, by their nature, are *human* (*i.e.*, fallible)
- Typical transcripts don’t contain everything an ASR system wants.
  - Where silence occurred; noises like coughs, door slams, etc.
  - Pronunciation information, *e.g.*, was *THE* pronounced as *DH UH* or *DH IY*?
How can we produce a more “complete” reference transcript?

Viterbi decoding!

Build HMM accepting all word (HMM) sequences consistent with reference transcript.

Compute best path/word HMM sequence.

Where does this initial acoustic model come from?
Another Way

- Just use the whole expanded graph during training.

- The problem: how to do context-dependent phone expansion?
  - Use same techniques as in building graphs for decoding.
Where Are We?

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Prerequisites

- Audio data with reference transcripts.
- What two other things?
The Training Recipe

- Find/make baseforms for all words in reference transcripts.
- Train single Gaussian models (flat start; many iters of FB).
- Do mixture splitting, say.
  - Split each Gaussian in two; do many iterations of FB.
  - Repeat until desired number of Gaussians per mixture.
- (Use initial system to refine reference transcripts.)
  - Select pronunciation variants, where silence occurs.
  - Do more FB training given refined transcripts.
- Build phonetic decision tree.
  - Use CI model to align training data.
- Seed CD model from CI; train using FB or Viterbi EM.
  - Possibly doing more mixture splitting.
How Long Does Training Take?

- It’s a secret.
- We think in terms of real-time factor.
  - How many hours does it take to process one hour of speech?
Whew, That Was Pretty Complicated!

- Adaptation (VTLN, fMLLR, mMLLR)
- Discriminative training (LDA, MMI, MPE, fMPE)
- Model combination (cross adaptation, ROVER)
- Iteration.
  - Repeat steps using better model for seeding.
  - Alignment is only as good as model that created it.
Things Can Get Pretty Hairy
Recap: Acoustic Model Training for LVCSR

- Take-home messages.
  - Hidden model training is fraught with local minima.
  - Seeding more complex models with simpler models helps avoid terrible local minima.
  - People have developed many recipes/heuristics to try to improve the minimum you end up in.
  - Training is insanely complicated for state-of-the-art research models.

- The good news . . .
  - I just saved a bunch on money on my car insurance by switching to GEICO.
Outline

- Part I: The LVCSR acoustic model.
- Part II: Acoustic model training for LVCSR.
- Part III: Decoding for LVCSR (inefficient).
  - Part IV: Introduction to finite-state transducers.
- Part V: Search (Lecture 8).
  - Making decoding for LVCSR efficient.
Course Feedback

1. Was this lecture mostly clear or unclear? What was the muddiest topic?

2. Other feedback (pace, content, atmosphere)?