11-830 Computational Ethics for NLP

Lecture 11: Privacy and Anonymity

Carnegie Mellon University
Language Technologies Institute

Privacy and Anonymity

- Being on-line without giving up everything about you
- Ensuring collected data doesn’t reveal its users data
- Privacy in
  - Structured Data: k-anonymity, differential privacy
  - Text: obfusticating authorship
  - Speech: speaker id and de-identification

Companies Getting Your Data

- They actually don’t want your data, they want to upsell
  - They want to be able to do tasks (recommendations)
  - They actually don’t care about the individual you
- Can they process data to never have identifiable content
  - Cumulated statistics
  - Averages, counts, for classes
- How many examples before it is anonymous

k-anonymity

- Latanya Sweeney and Pierangela Samarati 1998
- Given some table for data with features and values
- Release data that guarantees individuals can’t be identifyied
  - **Suppresion:** Delete entries that are too “unique”
  - **Generalization:** relax specificness of fields,
  - e.g. age to age-range or city to region

k-anonymity

Name	Age	Gender	State of domicile	Religion	Disease
Ramsha	29	Female	Tamil Nadu	Hindu	Cancer
Yadu	24	Female	Kerala	Hindu	Viral infection
Salima	28	Female	Tamil Nadu	Muslim	TB
Sunny	27	Male	Karnataka	Parsi	No illness
Joan	24	Female	Kerala	Christian	Heart-related
Bahuksana	23	Male	Karnataka	Buddhist	TB
Rambha	19	Male	Kerala	Hindu	Cancer
Kishor	29	Male	Karnataka	Hindu	Heart-related
Johnson	17	Male	Kerala	Christian	Heart-related
John	19	Male	Kerala	Christian	Viral infection

- From wikipedia: K-anonymity

k-anonymity

Name	Age	Gender	State of domicile	Religion	Disease
*	20 < Age ≤ 30	Female	Tamil Nadu	*	Cancer
*	20 < Age ≤ 30	Female	Kerala	*	Viral infection
*	20 < Age ≤ 30	Female	Tamil Nadu	*	TB
*	20 < Age ≤ 30	Male	Karnataka	*	No illness
*	20 < Age ≤ 30	Female	Kerala	*	Heart-related
*	20 < Age ≤ 30	Male	Karnataka	*	TB
*	Age ≤ 20	Male	Kerala	*	Cancer
*	20 < Age ≤ 30	Male	Karnataka	*	Heart-related
*	Age ≤ 20	Male	Kerala	*	Heart-related
*	Age ≤ 20	Male	Kerala	*	Viral infection

- From wikipedia: K-anonymity

k-anonymity

- But if X is in the dataset you do know they have a disease
- You can set “k” to something thought to be unique enough
- Making a dataset “k-anonymous” is NP-Hard
- But it is a measure of anonymity for a data set
- Is there a better way to hide identification?

Differential Privacy

- Maximize statistical queries, minimize identification
- When asked about feature x for record y
  - Toss a coin: if heads give right answer
  - If tails: throw coin again, answer yes if heads, no if tails
- Still has accuracy at some level of confidence
- Still has privacy at some level of confidence

Authorship Obfustication

- Remove most identifiable words/n-grams
  - “So” → “Well”, “wee” -> “small”, “If its not too much trouble” → “do it”
- Reddy and Knight 2016
  - Obfusticating Gender in Social Media Writing
  - “*omg I’m soooo excited!!!*”
  - “*dude I’m so stoked*”

Authorship Obfustication

- Most gender related words (Reddy and Knight 16)

	Twitter
Male	bro, bruh, game, man, team, steady, drinking, dude, brotha, lol
Female	my, you, me, love, omg, boyfriend, miss, mom, hair, retail
	Yelp
Male	wifey, wifes, bachelor, girlfriend, proposition, urinal, oem corvette, wager, fairways, urinals, firearms, diane, barbers
Female	hubby, boyfriend, hubs, bf, husbands, dh, mani/pedi, boyfriends bachelorette, leggings, aveda, looooove, yummy, xoxo, pedi, bestie

Authorship Obfustication

- Learning substitutions
  - Mostly individual words/tokens
  - Spelling corrections “goood” → “good”
  - Slang to standard “buddy” → “friend”
  - Changing punctuation
- But
  - Although it obfusticates, a new classifier might still identify differences
  - It really only does lexical substitutions (authorship is more complex)

Speaker ID

- Your speech is as true as a photograph
- Synthesis can (often) fake your voice
- Court case authentication
  - (usually poor recording conditions)
  - Human experts vs Machines
- Probably records exist for all your voices

Who is speaking?

- Speaker ID, Speaker Recognition
- When do you use it
  - Security, Access
  - Speaker specific modeling
    - Recognize the speaker and use their options
  - Diarization
    - In multi-speaker environments
    - Assign speech to different people
    - Allow questions like did Fred agree or not.

Voice Identity

- What makes a voice identity
  - Lexical Choice:
    - Woo-hoo,
    - I'll be back ...
  - Phonetic choice
  - Intonation and duration
  - Spectral qualities (vocal tract shape)
  - Excitation

Voice Identity

- What makes a voice identity
  - Lexical Choice:
    - Woo-hoo,
    - I'll be back …
  - Phonetic choice
  - Intonation and duration
  - Spectral qualities (vocal tract shape)
  - Excitation
- But which is most discriminative?

GMM Speaker ID

- Just looking at spectral part
  - Which is sort of vocal tract shape
- Build a single Gaussian of MFCCs
  - Means and Standard Deviation of all speech
  - Actually build N-mixture Gaussian (32 or 64)
- Build a model for each speaker
- Use test data and see which model its closest to

GMM Speaker ID

- How close does it need to be?
  - One or two standard deviations?
- The set of speakers needs to be different
  - If they are closer than one or two stddev
  - You get confusion.
- Should you have a “general” model
  - Not one of the set of training speakers

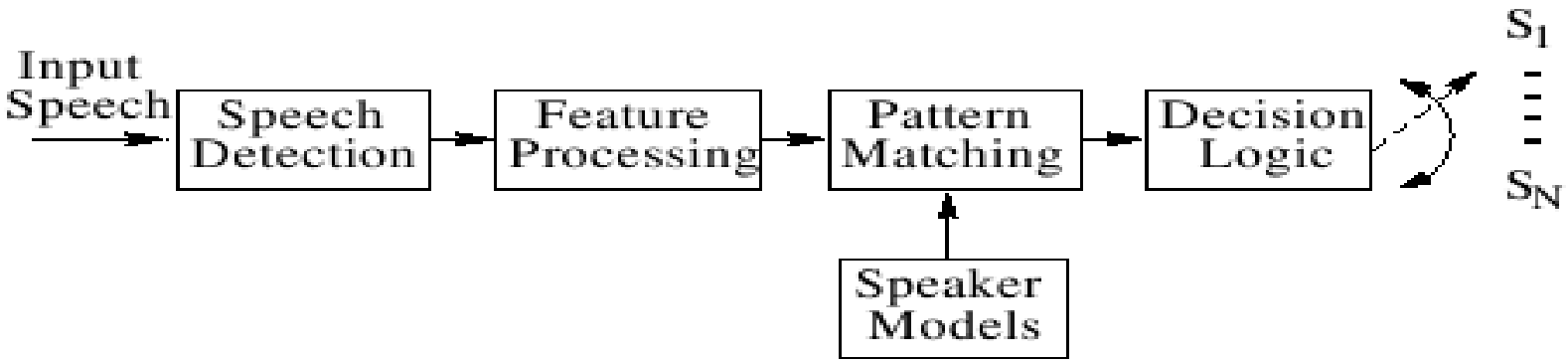
GMM Speaker ID

- Works well on constrained tasks
  - In similar acoustic conditions
  - (not telephone vs wide-band)
  - Same spoken style as training data
  - Cooperative users
- Doesn’t work well when
  - Different speaking style (conversation/lecture)
  - Shouting whispering
  - Speaker has a cold
  - Different language

Speaker ID Systems

- Training
  - Example speech from each speaker
  - Build models for each speaker
  - (maybe an exception model too)
- ID phase
  - Compare test speech to each model
  - Choose “closest” model (or none)

Basic Speaker ID system



Accuracy

- Works well on smaller sets
  - 20-50 speakers
- As number of speakers increase
  - Models begin to overlap – confuse speakers
- What can we do to get better distinctions

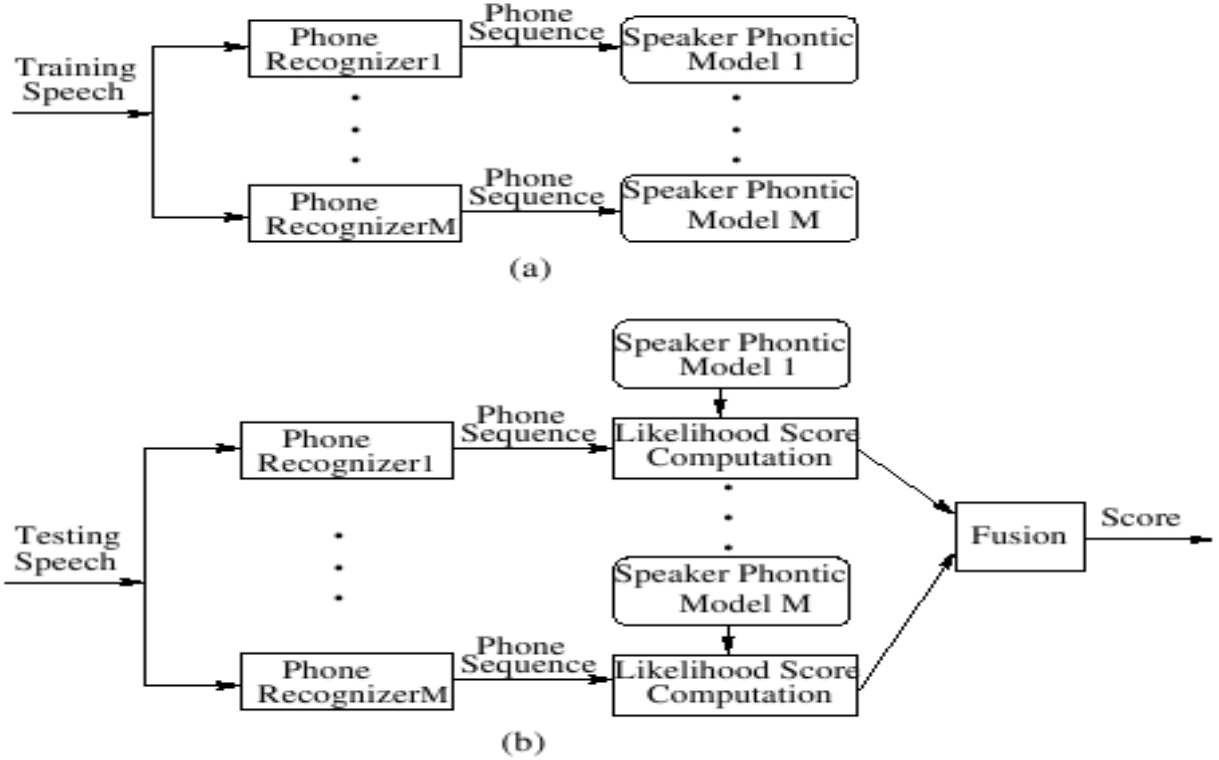
What about transitions

- Not just modeling isolated frames
- Look at phone sequences
- But ASR
  - Lots of variation
  - Limited amount of phonetic space
- What about lots of ASR engines

Phone-based Speaker ID

- Use *lots* of ASR engines
  - But they need to be different ASR engines
- Use ASR engines from lots of different languages
  - It doesn’t matter what language the speech is
  - Use many different ASR engines
  - Gives lots of variation
- Build models of what phones are recognized
  - Actually we use HMM states not phones

Phone-based SID (Jin)



Phone-based Speaker ID

- Much better distinctions for larger datasets
- Can work with 100 plus voices
- Slightly more robust across styles/channels

But we need more …

- Combined models
  - GMM models
  - Ph-based models
  - Combine them
  - Slightly better results
- What else …
  - Prosody (duration and F0)

Can VC beat Speaker-ID

- Can we fake voices?
- Can we fool Speaker ID systems?
- Can we make lots of money out of it?

- Yes, to the first two
  - Jin, Toth, Black and Schultz ICASSP2008

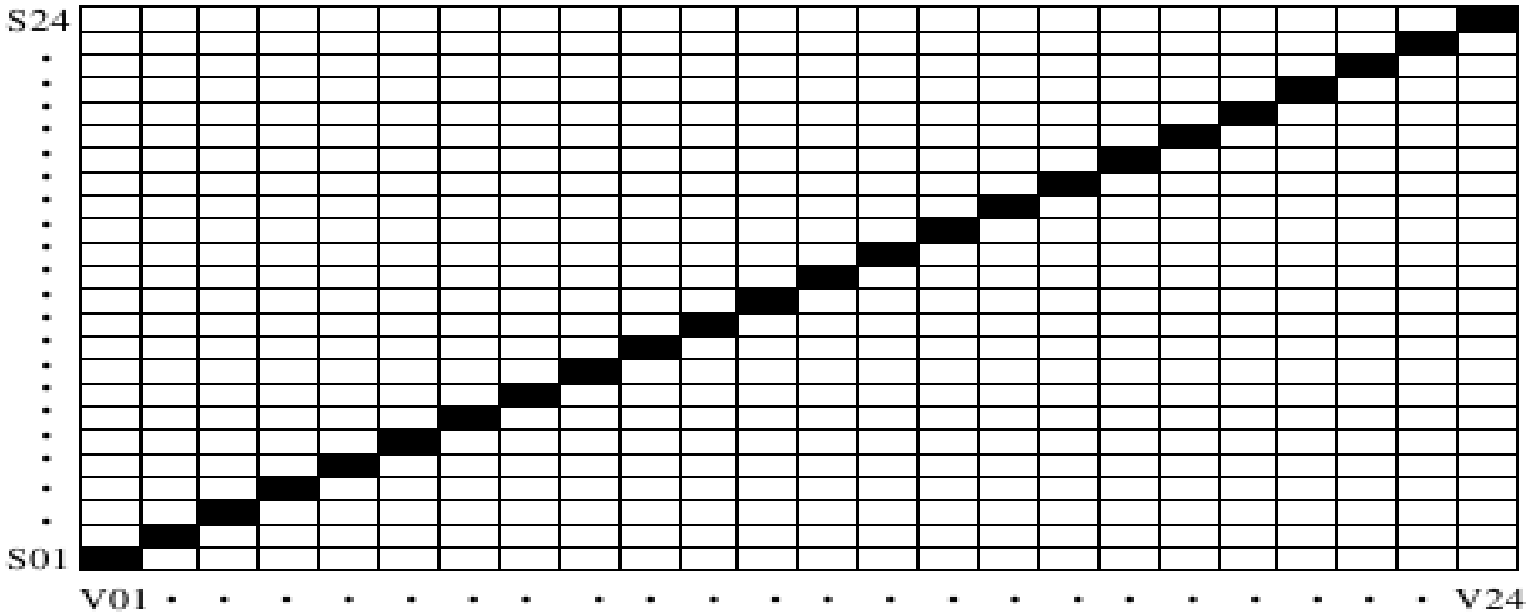
Training/Testing Corpus

- LDC CSR-I (WSJ0)
  - US English studio read speech
  - 24 Male speakers
  - 50 sentences training, 5 test
  - Plus 40 additional training sentences
  - Sentence average length is 7s.
- VT Source speakers
  - Kal_diphone (synthetic speech)
  - US English male natural speaker (not all sentences)

Experiment I

- VT GMM
  - Kal_diphone source speaker
  - GMM train 50 sentences
  - GMM transform 5 test sentences
- SID GMM
  - Train 50 sentences
  - (Test natural 5 sentences, 100% correct)

GMM-VT vs GMM-SID

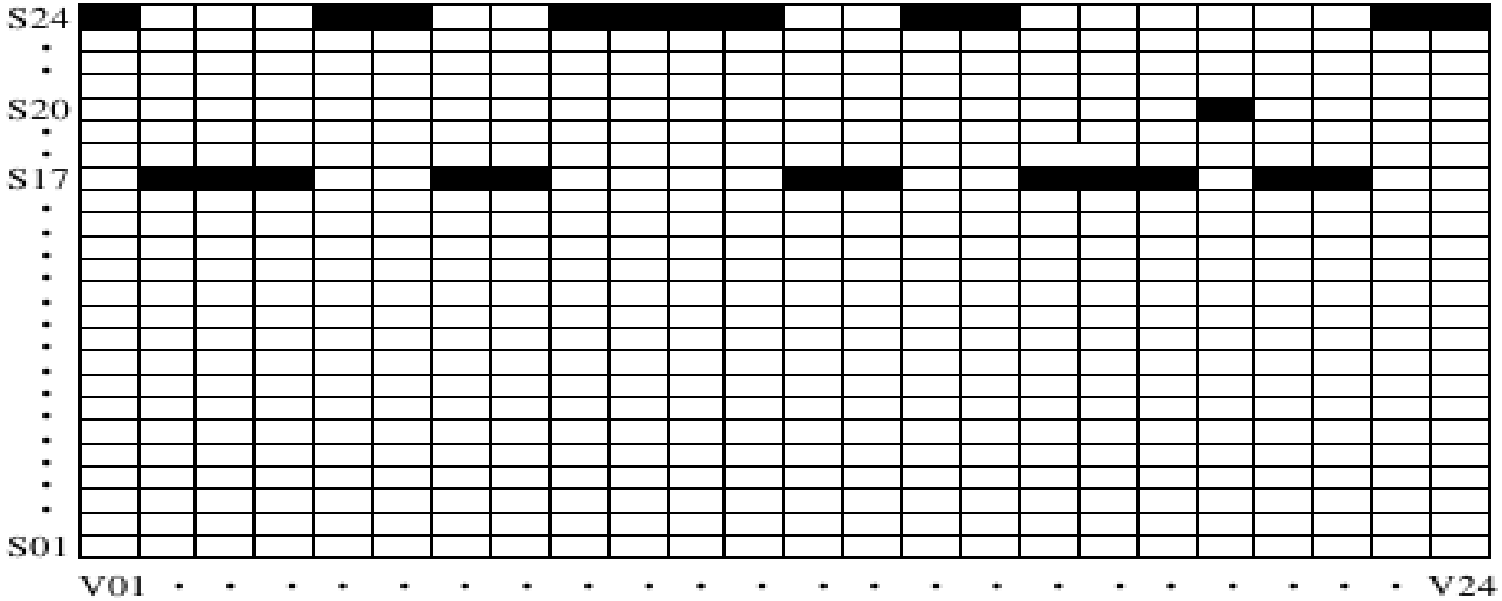


- *VT fools GMM-SID 100% of the time*

GMM-VT vs GMM-SID

- Not surprising (others show this)
  - Both optimizing spectral properties
- These used the same training set
  - (different training sets doesn't change result)
- VT output voices sounds "bad"
  - Poor excitation and voicing decision
- Human can distinguish VT vs Natural
  - Actually GMM-SID can distinguish these too
  - If VT included in training set

GMM-VT vs Phone-SID

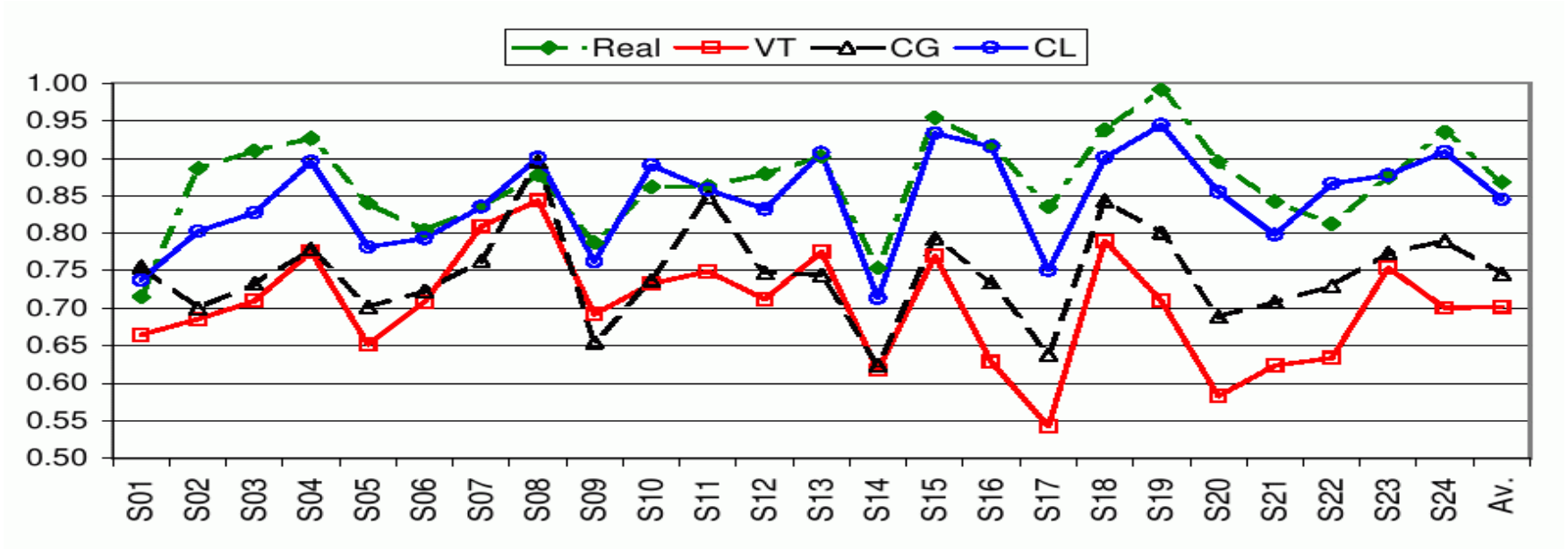


- *VT is always S17, S24 or S20*
- *Kal_diphone is recognized as S17 and S24*
- *Phone-SID seems to recognized **source** speaker*

and Synthetic Speech?

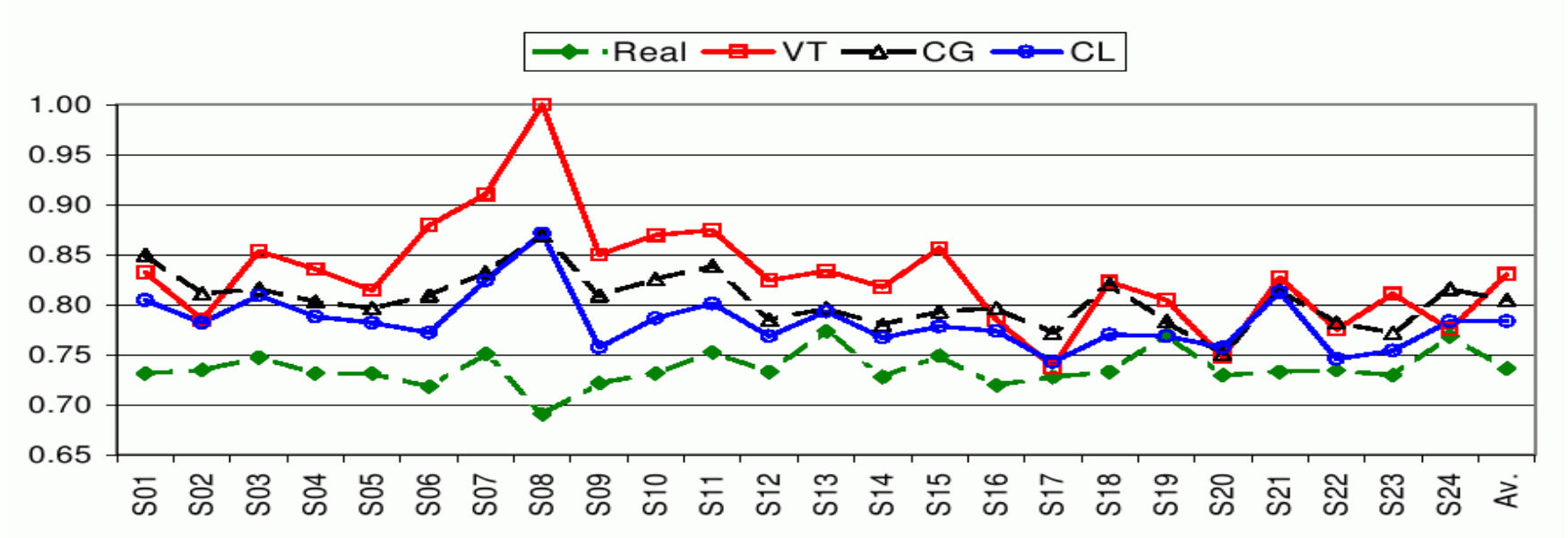
- Clustergen: CG
  - Statistical Parametric Synthesizer
  - MLSA filter for resynthesis
- Clunits: CL
  - Unit Selection Synthesizer
  - Waveform concatenation

Synth vs GMM-SID



- *Smaller is better*

Synth vs Phone-SID



- *Smaller is better*
- *Opposite order from GMM-SID*

Conclusions

- GMM-VT fools GMM-SID
- Ph-SID can distinguish source speaker
  - Ph-SID cares about dynamics
- Synthesis (pretty much) fools Ph-SID
  - We've not tried to distinguish Synth vs Real

Future

- Much larger dataset
  - 250 speakers (male and female)
  - Open set (include background model)
  - WSJ (0+1)
- Use VT with long term dynamics
  - HTS adaptation
  - articulatory position data
  - Prosodics (F0 and duration)
- Use ph-SID to tune VT model

Future II

- VT that fools Ph-SID
  - Develop X-SID (prosody?)
    - Develop X-VT that fools X-SID
      - Develop X2-SID
        - Develop X2-VT that fools …

        …..

De-identification

- Using Speaker ID to score de-identification
  - Reverse of voice transformation
    - Masking source, rather than being like target
- Simplest view
  - Full ASR and TTS in new engine (two hard)
- Voice conversion to synthetic voice
  - Natural speech to TTS (kal_diphone)

De-identification

- Morph your voice to something else
- Use voice conversion technology
- Mostly works (for spectral/phonetic information)
  - But what about words?
  - But what about timing/location/source

Future

- Advisorial Development
  - ID, counter-ID, better ID, better counter-ID
- Evolution is a very strong function
- De-identification hides your voice
  - But hides the others' voices too
- We could just end up with the best bot

Always Listening ...

- Google Glass, Amazon Echo
  - Looks for keyword …
  - So listens all the time
  - (But doesn't upload to the cloud, probably)
- What happens to the data I give up
  - Sentences do get uploaded.
  - (Probably) protected partially
- What about hackers:
  - Malicious, legal and “legal”

So we're doomed!

- Can we have web services and privacy?

So we're doomed!

- Can we have web services and privacy?
- Maybe ...

Homomorphic Encryption

- Doing Arithmetic in the Encrypted domain.
- For example:
  - Electronic voting
  - Summing bank account values
- Pass the encrypted cumulated values
  - Sum them in the encrypted domain
  - st. unencrypt(a')+unencrypt(b') =
    unencrypt(a' “+” b')

Homomorphic Encryption

- No unencrypted data is given to the server
- e.g.
  - HIPAA requirements:
    - → ASR without revealing the content
  - Can search encrypted calls from Terrorist without (unencrypted) access to non-Terrorist calls
- Can still update general models (ish)

Homomorphic Encryption

- Privacy Preserving Speech Processing (Manas Pathak 2012)
- Keyword spotting and HMM Recognition
- Great, where can I download it ...

Homomorphic Encryption

- Privacy Preserving Speech Processing (Manas Pathak 2012)
- Its computational **very** expensive
- (300-3000 times slower)
- It requires transfer of much more data

So We're Saved

- Maybe:
- We have to trust the makers for cryptography
- We have to do develop new anticryptography
- We have to be vigilant
  - (dont check you private keys into github)