#### Speech Synthesis

#### Text-to-speech (TTS)

#### Definition: a text-to-speech system must be

- Able to read any text
- Intelligible
- Natural sounding
- The first of these puts a constraint on the method we can choose:
  - playback of whole words or phrases in not a solution
- The second is actually closer to being a 'solved problem' than the third

#### <u>A generation task</u>

• although not completely clear what objective function we are optimising





# From linguistic specification to a waveform

• Concatenation builds up the utterance from units of recorded speech:

• Generation uses a model to generate the speech:



could be a sequence of HMMs, or a single DNN

# Synthetic speech created from audiobooks



#### DNN speech synthesis





Vocoder parameters



Linguistic features



#### Speech Synthesis: open problem 1

From input feature engineering (traditional NLP and knowledge sources)

to

learned-from-data linguistic features

# Standard text processing pipeline

linguistic specification



text

## Text processing pipeline

- A chain of **processes**
- Each process is performed by a **model**
- These models are independently trained in a supervised fashion on annotated data



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- Part-of-speech tagger
- Accuracy is very high
- <u>But</u>
  - trained on **annotated** text data
  - **categories** are designed for text, not speech



NP Public NPSAffairs NP Institute IN at NP U-Mass NP Boston, NP Doctor NP Ed NP Beard, VBZsays DT the NN push TN for VBPdo PP it. PP yourself



- Pronunciation model
  - dictionary look-up, *plus*
  - letter-to-sound model
- <u>But</u>
  - need deep knowledge of the language to design the phoneme set
  - human **expert** must write dictionary

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```
AHO
ADY
            TY()
     FΥ
AD7
     AE1
            -7
          D
    EY1
AF.
        THO JH TY1 AHO N
AEGEAN
AEGTS
       TY1 JH AHO S
            G AAO
AEGON
       EY1
                  N
AELTUS AE1 L T AHO S
AENEAS AE1 N TYO AHO
                        S
        AHO N IY1 IHO
AENEID
                        D
            EY1 K W IHO T R AAO N
AEOUITRON
AER
     EH1 R
AERTAL.
        EH1 R TYO AHO L
         EH1 R TYO AHO L Z
AERTALS
AERIE
       EH1 R TYO
        EH1 R IYO AHO N
AERTEN
         EH1 R TYO AHO N Z
AERTENS
AERTTALTA
            EH2 R THO T AE1 L Y AHC
      EH1 R OWO
AERO
```







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- Phrase-break prediction
  - binary classifier using POS sequence as input
- <u>But</u>
  - trained on **annotated** spoken data
  - therefore very **small** training set







ADTNBnineteen-CDNBeighteenCDNBstateNNNBconstitutionalJJNBamendmentNNB



NB

B

JJ

NN

This sequence is the annotated training data for our phrase break predictor

# Representing linguistic features

Vocoder parameters



Encoding

- 1-of-N for phoneme identity, POS, etc
- binary partitions of the space, e.g. "is this a vowel"
- positional features
  - within syllable, word, phrase

#### Representing context

- include previous & next phonemes, etc
- some features span the current utterance

#### Problems

- sparsity (mostly zeros)
- noise (errors in linguistic processing)
- relevance (not all features are predictive of speech)

## Learning embeddings of features



#### Stacking up more context



#### Speech Synthesis: open problem 2

From frame-by-frame prediction

to

trajectory generation

#### Frame-by-frame prediction



### Inconsistency



### Trajectory generation



#### Speech Synthesis: open problem 3

From **speaker-dependent** speech synthesis

to

adaptable and controllable models

Lots of work already on this in the HMM framework, but still remains an open problem for DNNs

### Different ways to adapt the DNN



#### Speech Synthesis: open problem 4

From output feature engineering (speech signal modelling, a.k.a vocoding)

to

learned-from-data speech generation

#### What to predict?



Linguistic features

