Speech Processing with Deep Learning

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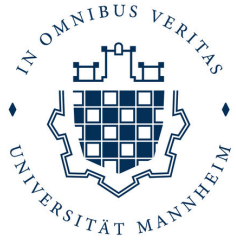
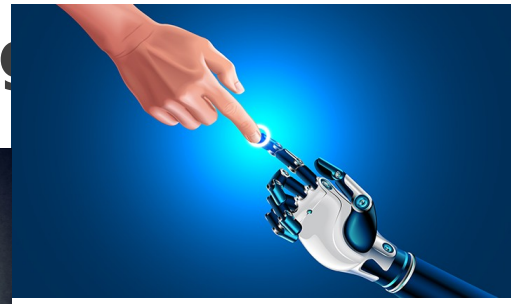


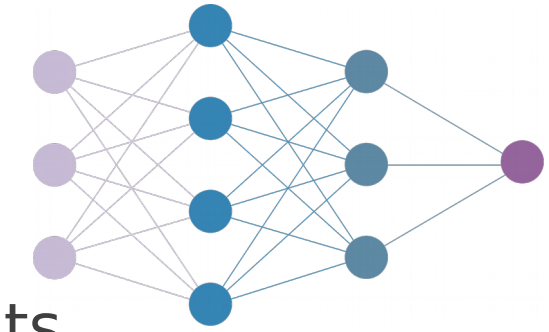
Agenda

1. Introduction
2. Preprocessing
3. Automatic Speech Recognition
4. Postprocessing
5. Demo
6. Conclusion

Speech Processing - First Question WHY

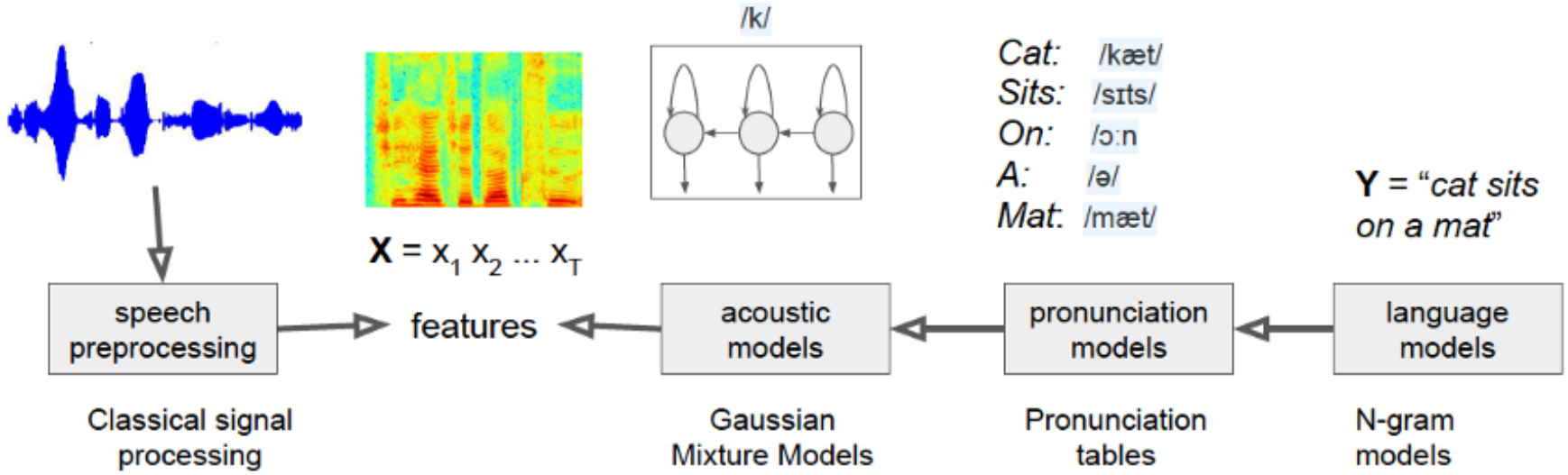
- **WHY Speech Processing**





- **WHY using NN**
  1. Language is complicated -> Dialects
  2. nothing sounds similar -> pronunciation
  3. depends on who is speaking -> Understand also people never heard speaking before
  4. need of using context to “understand”

Speech Processing - an Introduction



heartbeat.fritz.ai

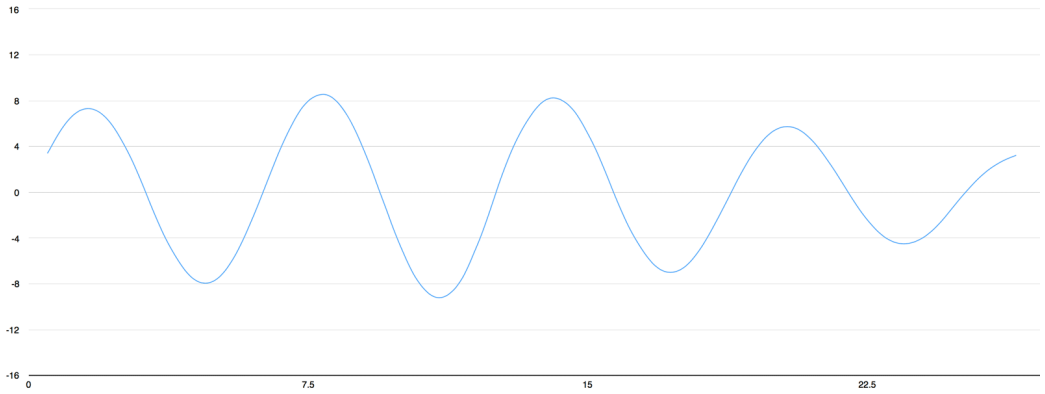
Preprocessing

First step: Feed sound waves into the computer

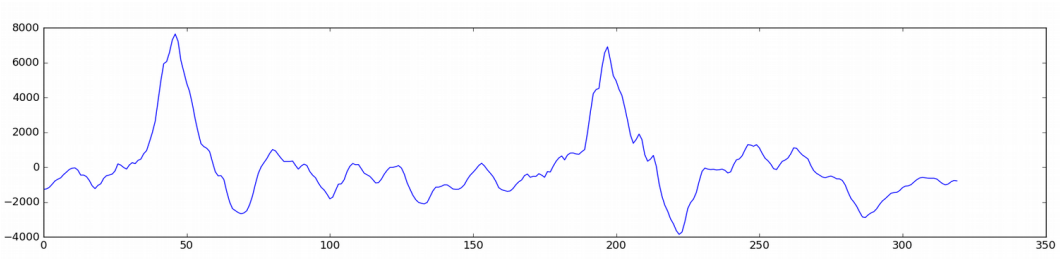
1. Turn Soundwave into numbers

2. Record the height of the wave at equally spaced points

   → Also knowns as sampling

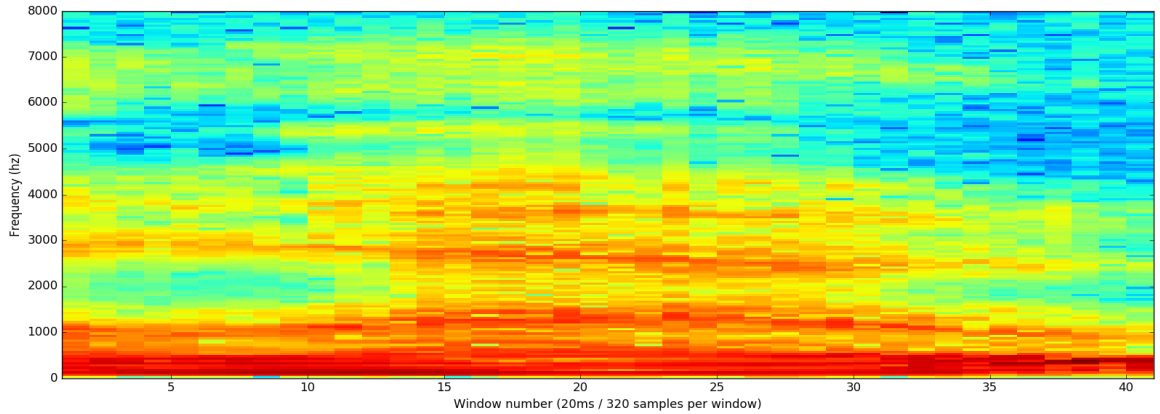


Sampling



23.2346566756,45.2314534534, 12.123254 ...

Preprocessing

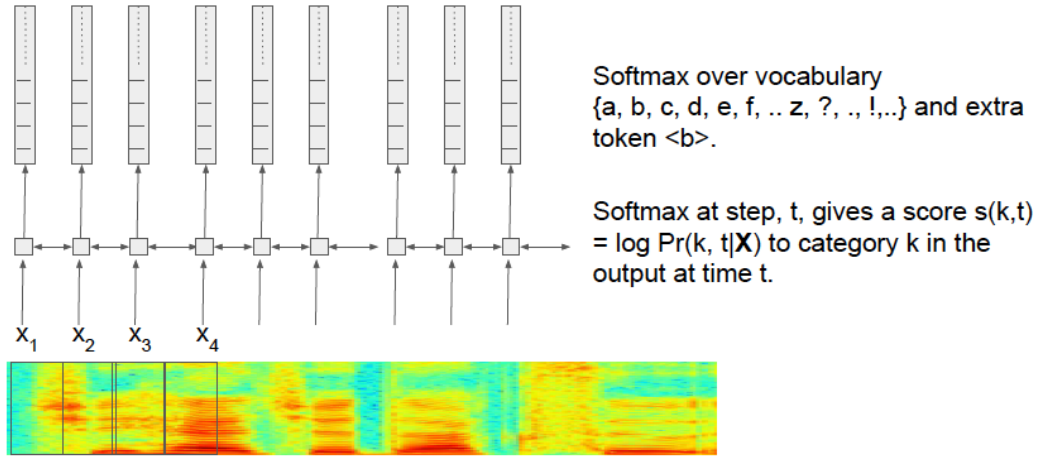


Transformation to a spectrogram

Automatic Speech Recognition

Acoustic Model

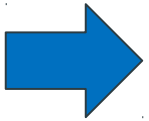
- Deals with the audio waveforms predicting what phoneme each waveform corresponds to
- Many approaches exists (Usually neural network, but N-gram possible)



Automatic Speech Recognition

Language Model

- Probability distribution over a word or word sequence
- Can base on probabilistic methods or neural networks



"I laik tu it" → "i like to eat"

Trigram Probability

Corpus: I am happy because I am learning

$$P(happy|I\ am) = \frac{C(I\ am\ happy)}{C(I\ am)} = \frac{1}{2}$$

Probability of a trigram: $$P(w_3|w_1^2) = \frac{C(w_1^2\ w_3)}{C(w_1^2)}$$

A fixed-window neural Language Model

output distribution

$$\hat{\boldsymbol{y}} = \text{softmax}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{b}_2) \in \mathbb{R}^{|V|}$$

hidden layer

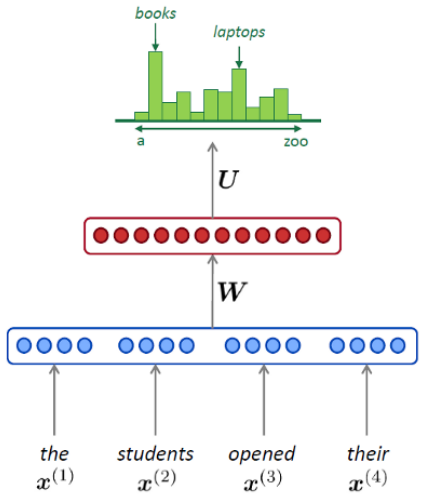
$$\boldsymbol{h} = f(\boldsymbol{W}\boldsymbol{e} + \boldsymbol{b}_1)$$

concatenated word embeddings

$$\boldsymbol{e} = [\boldsymbol{e}^{(1)}; \boldsymbol{e}^{(2)}; \boldsymbol{e}^{(3)}; \boldsymbol{e}^{(4)}]$$

words / one-hot vectors

$$\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \boldsymbol{x}^{(3)}, \boldsymbol{x}^{(4)}$$



Post-processing - considerations

- **punctuation restoration and capitalization**

`Let's eat, kids. ´ vs. `Let's eat kids. ´

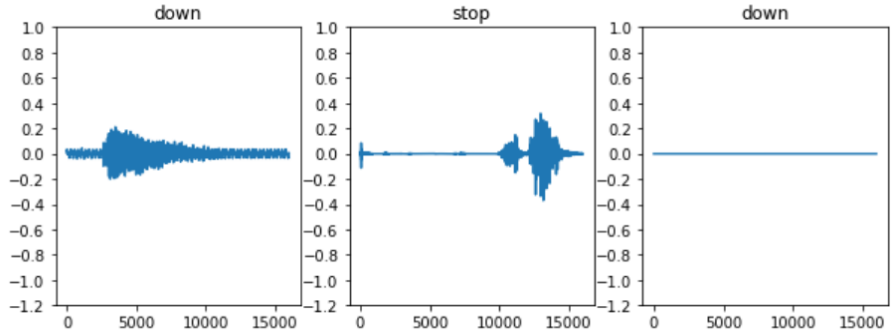
- **Ability to process unknown words**

→ as always **use preferably as little computational resource**

Demo

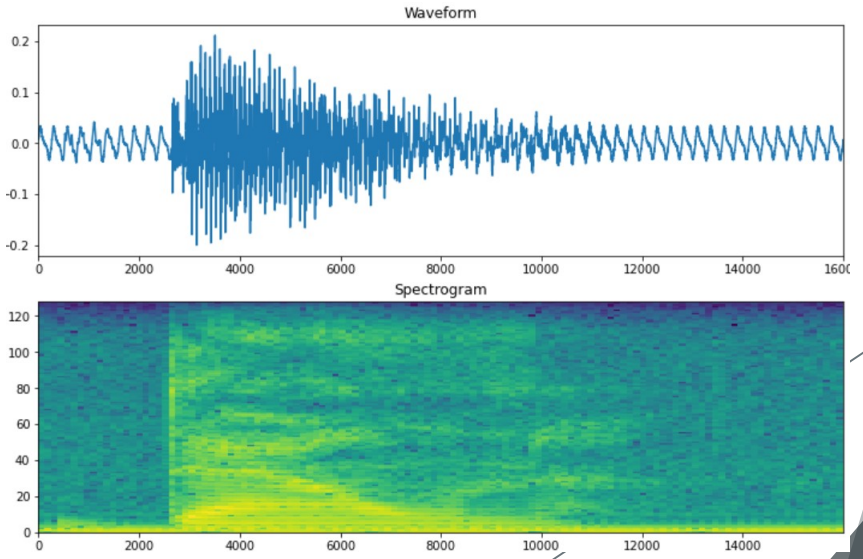
```
import seaborn as sns
import tensorflow as tf
```

```
rows = 3
cols = 3
n = rows*cols
fig, axes = plt.subplots(rows, cols, figsize=(10, 12))
for i, (audio, label) in enumerate(waveform_ds.take(n)):
  r = i // cols
  c = i % cols
  ax = axes[r][c]
  ax.plot(audio.numpy())
  ax.set_yticks(np.arange(-1.2, 1.2, 0.2))
  label = label.numpy().decode('utf-8')
  ax.set_title(label)

plt.show()
```



simple_audio.ipynb - Colaboratory (google.com)

```
def plot_spectrogram(spectrogram, ax):
  # Convert to frequencies to log scale and transpose so that the time is
  # represented in the x-axis (columns). An epsilon is added to avoid log of zero.
  log_spec = np.log(spectrogram.T+np.finfo(float).eps)
  height = log_spec.shape[0]
  width = log_spec.shape[1]
  X = np.linspace(0, np.size(spectrogram), num=width, dtype=int)
  Y = range(height)
  ax.pcolormesh(X, Y, log_spec)


fig, axes = plt.subplots(2, figsize=(12, 8))
timescale = np.arange(waveform.shape[0])
axes[0].plot(timescale, waveform.numpy())
axes[0].set_title('Waveform')
axes[0].set_xlim([0, 16000])
plot_spectrogram(spectrogram.numpy(), axes[1])
axes[1].set_title('Spectrogram')
plt.show()
```



Conclusion

Hey Siri

amazon alexa

Appendix

Post-processing - models

	+	-
n-gram based approach	fast results	- needs a lot of disk space - handling of out-of-vocabulary words
bidirectional RNN	high accuracy	size of input ↑ => time per token ↑

- **TruncBiRNN**
  - forwards normal RNN
  - backwards only a specified window is considered

Post-processing - models