Voice-enabled Internet of Things

Advanced Topics in Internet of Things

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Motivations

- IoT devices are all around your home
  - *Smart speakers*: Amazon Echo & Google Home
  - *Heating & cooling*: Nest Learning Thermostat & Ecobee4
  - *Smart locks & doors*: August Smart Lock & SkyBell HD
  - *Smart lightening*: Philips Hue & Lifx Color
  - *Cleaning*: iRobot Roomba, Neato Botvac
  - *Smart shades*: Lutron's Serena Shades
  - *Security cameras*: Amazon Cloud Cam & Nest Protect

- Ways to communicate with IoT devices:
  - *Graphical User Interface (GUI)*:

    - Pushing buttons
    - Clicking on icons
  - *Speech Interfaces*:

    - Just talking to the device which is more intuitive and efficient
    - Speech processing and natural language processing empowers these interfaces

Motivations (Continued)

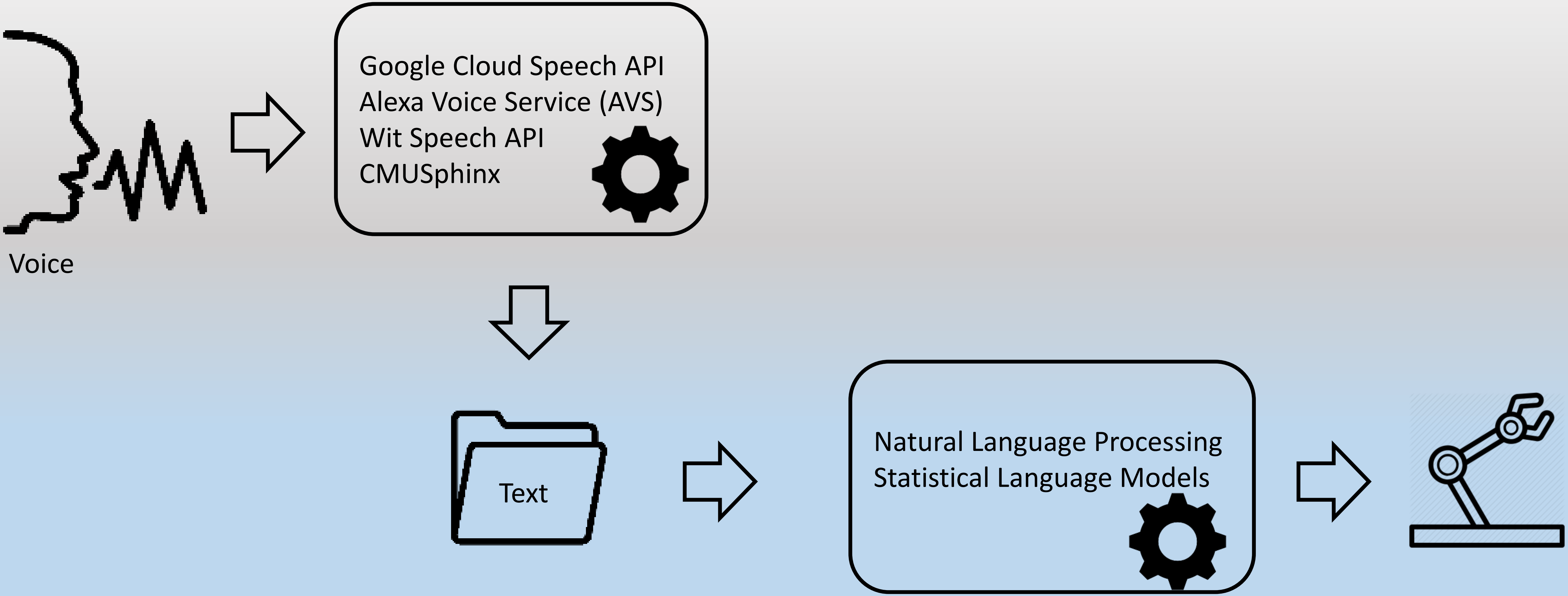
- **Limitations** of the current smart home IoT devices (e.g. a smart speaker)
  1. Most of smart home devices are not customizable and customers cannot extend them to have their customized voice commands or tune their accuracy
  2. Smart home speakers cannot handle complex scenarios such as:
     1. They fail processing combined commands separated by “and”.
     2. They fail processing two concurrent commands

- **Contributions** of this project is two folds:
  1. Building a customizable voice-enabled IoT device
  2. Proposing a solution for handling two concurrent voice commands to a voice-enabled IoT device

A Customizable Voice-enabled IoT Device

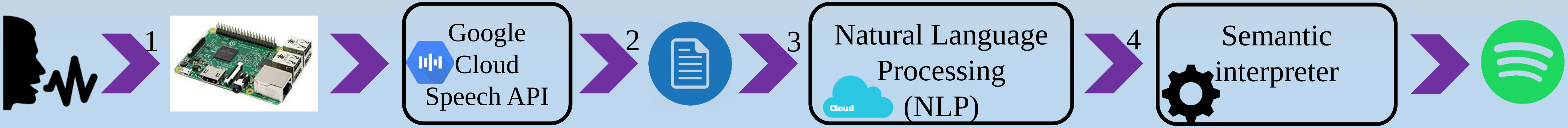
Blind Source Separation for Voice-enabled IoT

How Speech recognition works for IoT



Proposed Customizable Voice-enabled IoT Device

- The proposed model consists of the following components:
  1. We use a small USB microphone that captures the incoming voice
  2. We use Google Cloud Speech API which is free for developers
  3. We use a simple Natural Language Processing (NLP) model to create a language model for playing music
  4. We use the inferred intent on the target device to play/pause the music



1. Recorded human voice, e.g. voice saying “Play music for me.”

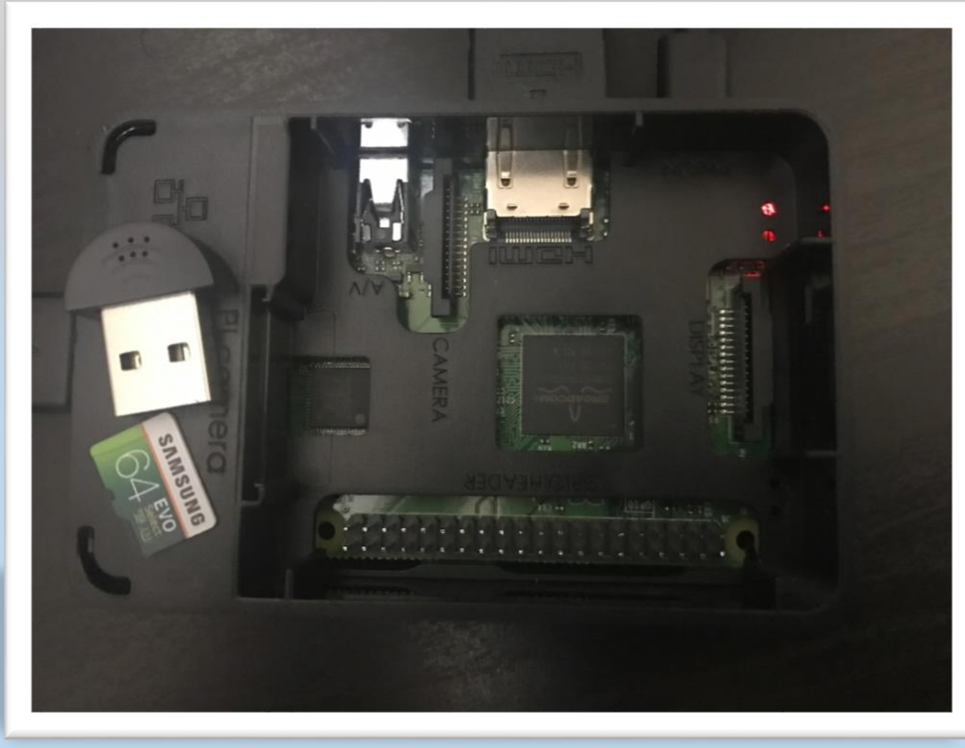
2. Plain text, e.g. text saying “Play music for me.”

3. Extract the intent, e.g. action “play music”, sub-action “music”, and device “Spotify”

4. Execute the intent, e.g. call Spotify API to play music

Introducing Voice-enabled IoT Device

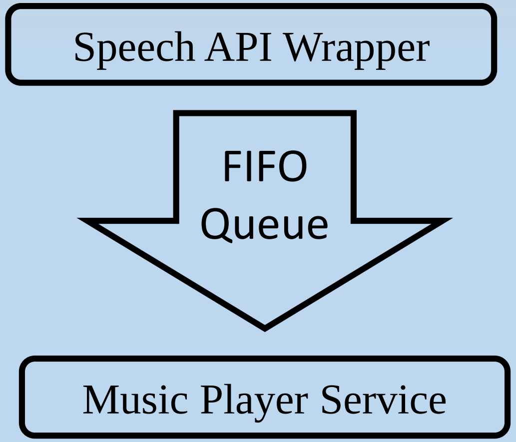
- The total cost of building the prototype is **$68.42** and consists of the following two building blocks:
- The hardware components of the customized IoT device:
  - Raspberry Pi 3 Model B Motherboard, $35.80
    - Quad core Cortex A53 @ 1.2GHz
    - 1GB SDRAM
    - Wireless 802.11
    - Bluetooth 4.0
  - Kinobo USB 2.0 Mini Microphone, $4.65
  - Samsung 64GB Micro SD Card, $19.99
  - Raspberry Pi Case, $7.98



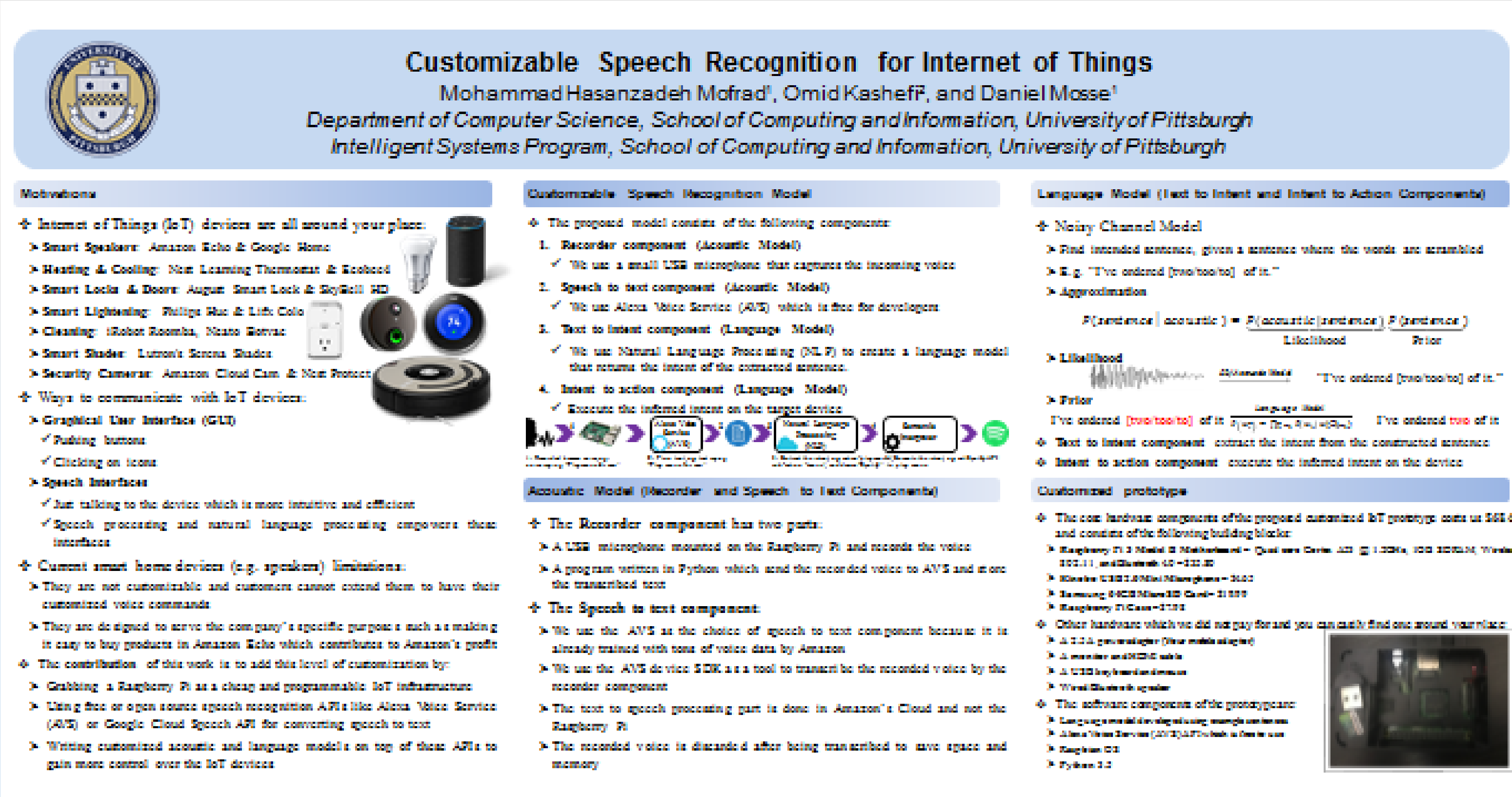
Introducing Voice-enabled IoT Device

- The total cost of building the prototype is **$68.42** and consists of the following two building blocks:
  - Other hardware which we did not pay for and you can easily find one around your place:
    - A 2.5A power adaptor (mobile adaptor)
    - A monitor and HDMI cable
    - A USB keyboard and mouse
    - Wired/Bluetooth speaker

- The software components of the prototype are:
  - Google Cloud Speech API which is free to use
  - Raspbian OS
  - Python 3.5



Demo of Voice-enabled IoT Device

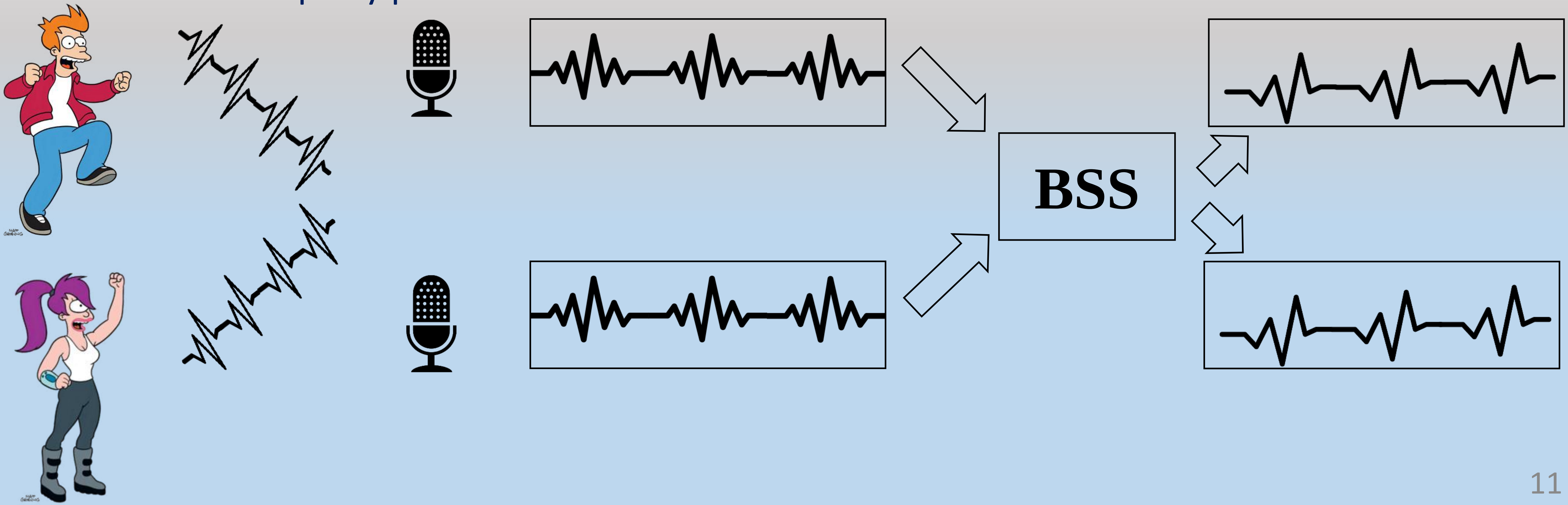


A Customizable Voice-enabled IoT Device

Blind Source Separation for Voice-enabled IoT

Blind Source Separation (BSS)

- Blind Source Separation is the separation of a set of source signals from a set of mixed signals without knowing about the mixing process of source signals.
  - Cocktail party effect
  - Cocktail party problem



A Customizable Voice-enabled IoT Device

Blind Source Separation for Voice-enabled IoT

Reconstruction Independent Component Analysis (RICA)

Reconstruction Independent Component Analysis (RICA)

- Independent Component Analysis (ICA) is a method for separating a multivariate signal into its component with the assumption of:
  - Subcomponents are non-Gaussian
  - Subcomponents are statistically independent
- ICA is a special case of blind source separation
- RICA algorithm is based on minimizing an objective function.
  - Source model: $x = \mu + As$ where
    - $x_{p \times 1}$ mixed signals
    - $\mu_{p \times 1}$ offset values
    - $A_{p \times q}$ mixing matrix i.e. $p = q$
    - $s_{q \times 1}$ original signal
  - Source signal can be recovered by
    - $s = A^{-1}(x - \mu)$
  - Without knowing A and μ, given observations x_1, x_2, .., RICA extracts the original signal s_1, s_2, …

Quoc V. Le, et al. "ICA with Reconstruction Cost for Efficient Re Feature Learning." NIPS, 2011

Reconstruction Independent Component Analysis (RICA) (continued)

- RICA uses
  - A data matrix X

$$X_{n \times p} = [x_1^T, x_2^T, \ldots, x_n^T]^T \text{ i.e. } x_{i\; p \times 1}$$

    - Each row represents an observation and each column represents a measurement
  - An initial random weight matrix W

$$W_{p \times q} = [w_1, w_2, \ldots, w_q] \text{ i.e. } w_{i\; p \times 1}$$

- And optimizes

$$\Sigma\, g(XW) \text{ where } g = ½ \log(\cosh(2x))$$

  - The objective function h results in a minimal matrix W that transforms data X to XW

$$h = \lambda/n \, \Sigma^n_{i=1} \, ||WW^T x_i - x_i||^2_2 + 1/n \, \Sigma^n_{i=1} \Sigma^q_{j=1} \sigma_j g(w_j^T x_i)$$

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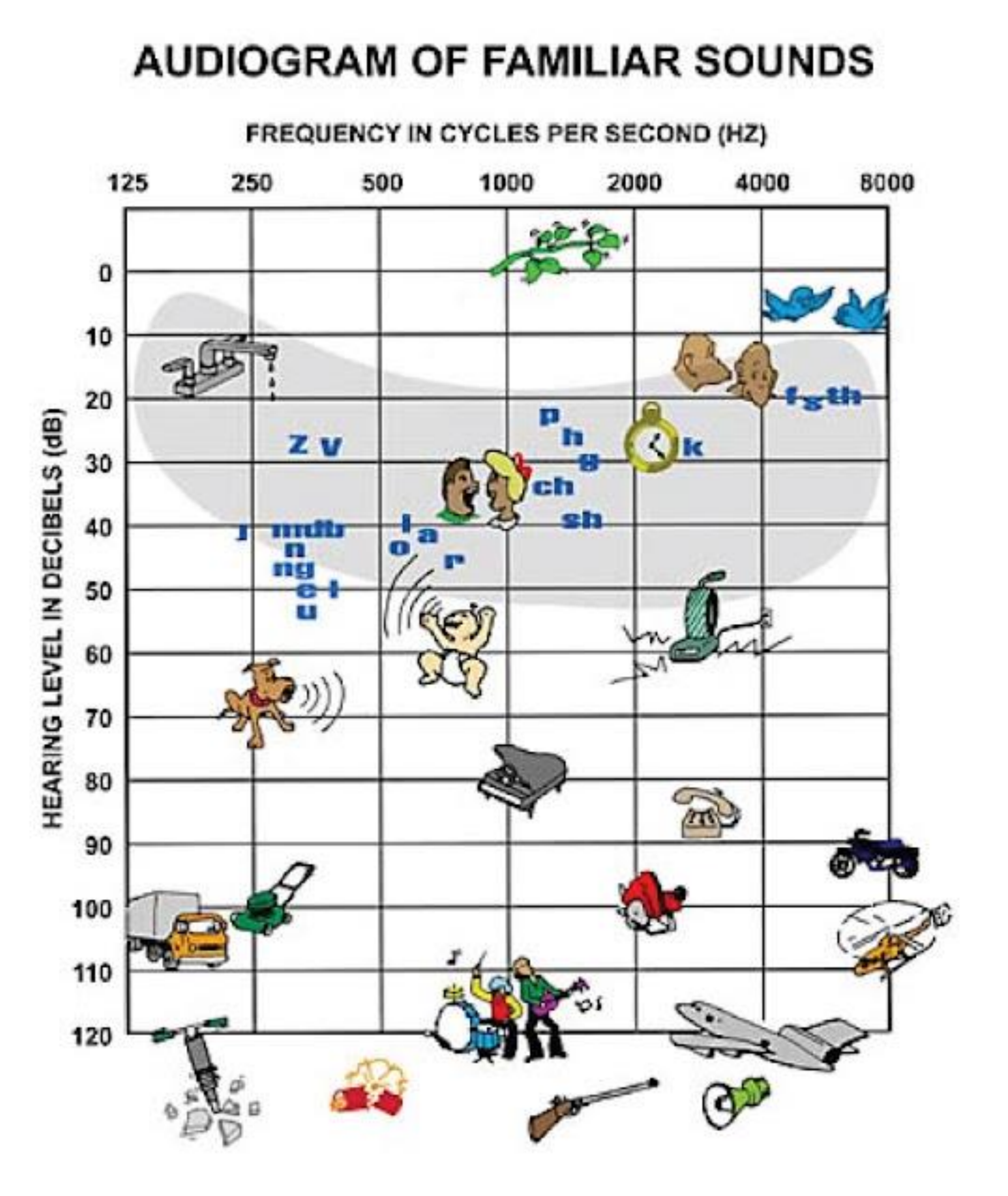
Reconstruction Independent Component Analysis (RICA)

Crossed Lowpass Filter

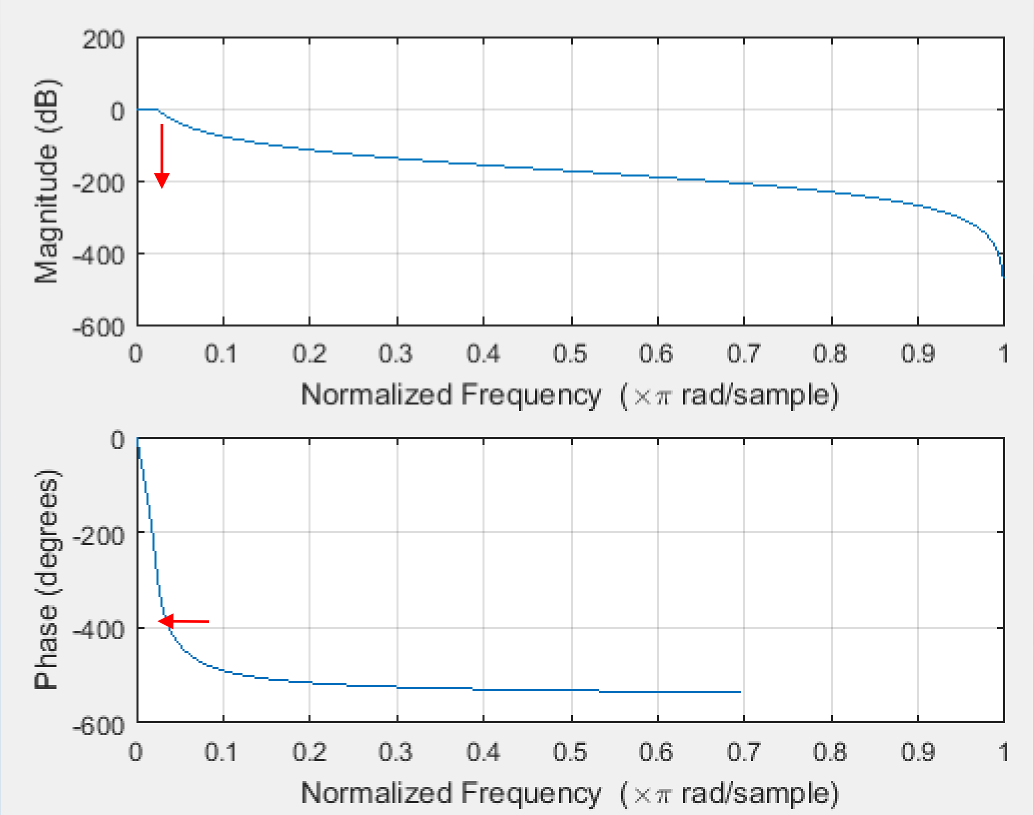
Lowpass Filter

- Lowpass filter
  - Allows signals below a cutoff frequency (passband)
  - Attenuates signals above the cutoff frequency (stopband)
- By removing some frequencies, the lowpass filter smooths the signal.
- Hearing frequency range
  - The frequency of human voice is between 100 Hz and 8 KHz
  - The fundamental frequency is 100 Hz to 900Hz

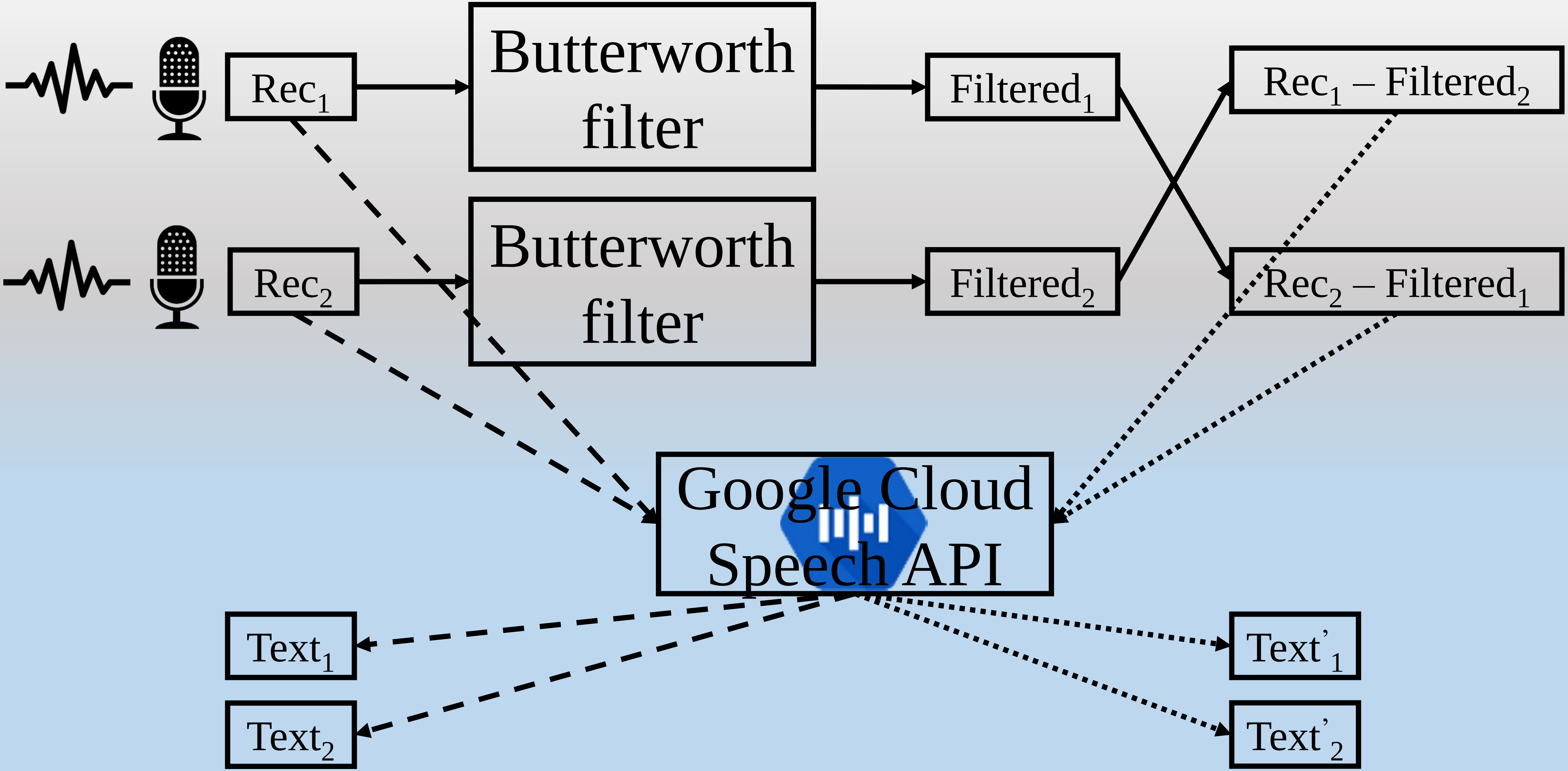


Lowpass Filter Design

- Filter design: Butterworth filter
  - Butterworth filter completely reject the unwanted frequencies
  - Butterworth filter has uniform sensitivity for the wanted frequencies
- Filter details
  - The sample rate fs is 44100 Hz
  - The cutoff frequency fc is 500
  - $fc/(fs/2) = 0.023\pi$ rad/sample



Crossed Lowpass Filter



Transcription Accuracy

- Accuracy of transcription is calculated using
  - Accuracy = 1 - Word Error Accuracy (WER) i.e. WER

$$WER = (S + D + I) / (S + D + C) \text{ i.e.}$$

S = #Substitutions
D = #Deletions
I = #Insertions
C = #Corrects
N = #Words = S + D +C

- Models
  1. Baseline
  2. RICA
  3. Crossed Lowpass
- Recordings are annotated in a supervised manner and the ground-truth data is used to calculate WER for each model.

Results

Dataset 1:
30 different sentences
Pairs of sentences are recorded in the proximity of the microphone

Algorithm	Baseline	RICA	Crossed Lowpass
Mic_1	0.96	0.91	0.99
Mic_2	0.95	0.35	0.96
Total	0.95	0.63	0.97

Dataset 2:
44 different sentences
Pairs of sentences are recorded far from the proximity of the microphone

Algorithm	Baseline	RICA	Crossed Lowpass
Mic_1	0.96	0.95	0.98
Mic_2	0.44	0.18	0.47
Total	0.70	0.56	0.73

Conclusion

- The contributions of this project is two folds
  1. Building a voice-enabled IoT device comparable with smart speakers
     - Cost effective
     - Customizable
  2. Designing filters to improve the recognition power of existing speech-to-text APIs such as Google Cloud Speech API
     - *Adding a wrapper atop of Google Cloud Speech API which enables the API to process two concurrent commands which is not supported by the smart speakers right now.*
     - By enhancing the quality of the input speech signal , we were able to improve the performance of Google Cloud Speech API by 3%.

Questions

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