A Cascade Architecture for Keyword Spotting on Mobile Devices

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Abstract

We present a cascade architecture for keyword spotting with speaker verification on mobile devices. By pairing a small computational footprint with specialized digital signal processing (DSP) chips, we are able to achieve low power consumption while continuously listening for a keyword.

1 Introduction

Voice assistants have become prevalent in the last few years. A common way to initiate a conversation with your assistant is via a keyword, such as "Ok Google", "Alexa", or "Hey Siri". Thus, it is important for the keyword to be available in as many devices as possible, many of them battery powered or with restricted computational capacity.

Keyword detection is like searching for a needle in a haystack: the detector must listen to continuously streaming audio, ignoring nearly all of it, yet still triggering correctly and instantly. On a mobile device, this is particularly challenging when considering that typical mobile devices (e.g. smartphones) have batteries with capacities between 1,000mAh and 2,400mAh, and thus in the best case our entire system must consume less than 1mA to consume less than 1% of the battery per day.

We present a cascade architecture for keyword spotting that can meet these power requirements, while achieving high accuracy. The first stage is comprised of a very small and power efficient detector that executes on a DSP. Upon trigger, it delegates the final detection decision to a second, much larger and more accurate detector, that executes on the device's main application processor (AP).

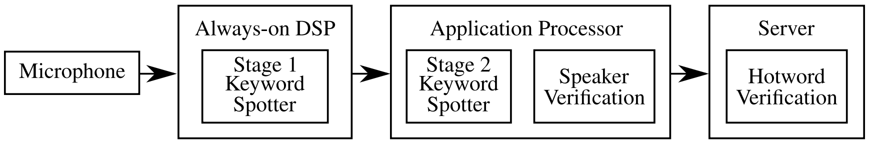
The following section gives an overview of the system. Subsequent sections describe our quantization approach, as well as a final stage of the pipeline that runs on the server. Finally we present accuracy results of the cascade system.

2 Architecture

Our system, shown in figure 1 is a cascade of two keyword detectors that trade-off computation and memory footprint (and thus power consumption), with accuracy. The first stage is very small and executes continuously, buffering enough audio to safely fit the keyword (typically 2 seconds). Upon detection it passes the audio buffer to the second stage, and continues to stream the audio that follows. The second stage uses uses a larger and more accurate model to make the final decision. The second stage also supports speaker verification, allowing only known speakers to trigger the keyword.

This cascade approach is advantageous regardless of where the execution takes place, however when running continuously it is impossible to meet the previously described power restrictions using a standard mobile AP. Thus, we utilize power-isolated memory and processor, typically in the form of a DSP, to execute the continuous first stage. The second stage, with more relaxed power constraints,

Figure 1: Cascade keyword spotting architecture



is both able to and required to execute a larger and better quality detection model to overcome the leniency of the first stage. However, computation is still quite important, as the second stage must be able to process the buffered audio coming from the first stage as fast as possible to minimize detection latency. Given this different set of requirements, we execute the second stage on the AP.

2.1 Anatomy of a keyword spotter

Our detectors receive the raw audio as input and produce a yes/no decision. Internally they are composed by three main components: 1) a signal processing frontend 2) a neural network acoustic encoder and 3) a decoder.

Frontend The frontend receives the audio signal and produces features for the encoder neural network. Its execution involves some typical signal processing algorithms, like spectral subtraction, but ultimately produces a log-mel filterbank (the log of the triangular mel filters applied to the power spectra). We typically use either 32 or 40 filterbank channels per 25ms frame.

Neural network acoustic encoder The encoder receives the filterbank channels from one or more stacked frames (depending on the neural network topology), and produces posterior probabilities for acoustic units from the keyword (e.g. phones or syllables). This component is what dominates both the computation as well as the ultimate quality of the system, and consequently it is where a lot of research has been focused on, iterating over several topologies and training setups [2, 3, 8] until arriving to the rank constrained topology proposed in [6].

Decoder The decoder receives the M posteriors for the acoustic units of the keyword, $\mathbf{y} = \{y_1, y_2, \cdots, y_M\}$, and produces a score $h(\mathbf{y})$ between 0 and 1. The score is computed by smoothing the posterior values, $s_t(y_i)$, by averaging them over a sliding window of the previous L frames with respect to the current t. The score is then defined as the largest product of the smoothed posteriors in the input sliding window, subject to the constraint that the individual units 'fire' in the same order as specified in the keyword, as described in [7] by the following formulation:

$$s_t(y_i) = \frac{1}{L}\sum_{j=t-L+1}^{t} y_{i,j}; \quad h(\mathbf{y}) = \left[\max_{1\leq t_1 \leq \cdots \leq t_M \leq T_s} \prod_{i=1}^{M} s_{t_i}(y_i)\right]^{\frac{1}{M}} \tag{1}$$

2.2 Speaker verification

On mobile devices, speaker verification is used so that the device responds only to its owner. It works by "enrolling" the speaker on N (typically 3) utterances of the keyword, creating a unique signature. At test time, the utterance, segmented by the second stage's keyword detector, is processed by the speaker verifier to generate another signature and compare it with that stored on-device, as described in [9]. The comparison, typically a cosine distance between the 2 signatures, will produce a score on which a threshold can be selected to determine verification status.

The speaker verifier is a neural network, typically an LSTM as in [4], which processes frames generated by the frontend, segmented by the second stage keyword detector. This neural network emits the speaker signature in the form of a vector of numbers.

2.3 Operating point selection

The accuracy of an individual detector, and of the cascade, is measured as a tradeoff between false accept rate (FAR) – triggering for audio not containing the keyword – and false reject rate (FRR) –

failing to trigger for audio containing the keyword. For the cascade to work properly, the first and second stage keyword detectors must be trained on the same data and have similar FRR. This way, instead of being additive, their combined FRR is very close to that of the second stage alone.

Since the first stage model is significantly smaller, it follows that its FAR must be higher than that of the first stage. The FAR is still quite important, as each run of the second stage will briefly draw 1 to 2 orders of magnitude more current. If the FAR of the first stage is too high, the combined power consumption will be significant. We are typically able to tune the first stage to only wake up a handful of times per hour, even when exposed continuously to speech.

Speaker verifications acts as a third filter. It contributes both to increasing the FRR (when it incorrectly rejects a keyword spoken by the enrolled speaker) and to decreasing the FAR. We find that the speaker verification can reduce the overall FAR by a factor of 5 to 10 while adding less than 1% absolute additional FRR, since keyword spotting false alarms from other people speaking, television shows, radio, etc are almost always rejected.

2.4 Considerations of the DSP implementation

Memory DSPs come in a variety of forms and specifications: they can be integrated as part of a system on chip (SoC), or connected externally. However a common trait is that in order to achieve power efficiency and to reduce cost, DSPs typically have small amounts of memory (e.g. 128kB is typical).

The available memory is split between code, working-buffers and any loaded artifacts (e.g. neural network models). In addition, to achieve low latency the model and code must be kept resident in memory at all times. This means, that code and model size are very important. Our system's program memory takes up approximately 25kB, plus another 12kB for things like fast Fourier transform (FFT) twiddle tables, leaving the rest of available memory to fit the model and the audio buffer. 2 seconds of 16bit mono PCM audio at a 16khz sample rate consumes 64kB. That means that given the aforementioned 128kB restriction, we have set the footprint of our first stage keyword model to 13kB.

Precision DSP platforms have their own instruction sets, thus each requires specialized optimization work. Moreover, as computation can vary from 16, 24, or 32 bits, and platform-specific optimization such as FFT and matrix multiplication can produce somewhat different results, we cannot guarantee that the computation done on each platform is bit identical.

This makes scaling to supporting multiple DSP platforms challenging, as we need to be able to guarantee correctness per platform. Moreover, differences in the signal processing frontend can sometimes be significant enough that training platform-specific neural networks becomes desirable.

To accommodate this, we use emulation libraries to produce bit identical behavior using standard C code, emulating the specifics of each platform. This way we can still perform large scale neural network training and evaluation, resulting in per-platform neural network models.

3 Quantization

In order to reduce the memory footprint of the neural network models, take advantage of the available fast integer operations (e.g. matrix multiplications), and cover the broadest range of DSPs, we transform the inputs, as well as the trained parameters of the neural network models from their original floating point representation into an integer based one (8 bit to be precise).

The parameter quantization itself can be defined as using a uniform linear quantizer that assumes a uniform distribution of the values within a given range. First, we find the minimum and maximum values of the original parameters. We then use a simple mapping formula which determines a scaling factor that when multiplied by the parameters spreads the values evenly in the smaller precision scale, thus obtaining a quantized version of the original parameters. We have slightly different approaches for executing inferences on the quantized models: as previously mentioned, on a DSP all execution is fixed point, whereas in the CPU we take advantage of floating point accumulators as proposed in [1].

Table 1: Cascade operating point as a function of the stage 1 operating point.

Stage 1 FA/hr	Stage 1 FRR	Cascade FA/hr	Cascade FRR
None	None	.03	3.1%
0.5	4.1%	0.006	5.6%
0.8	3.4%	0.006	5.1%
5.0	1.6%	0.02	3.8%
10.0	1.2%	0.02	3.5%

4 Server-side validation

A third, optional, stage occurs on the sever side as part of the full speech recognizer, which can further reduce the false accept rate [5]. In addition, the keyword spotter produces alignment information, which can improve start-of-speech detection. Because of this, and coarticulation effects, the overall word error rate can be improved on the query.

5 Results

Table 5 shows the accuracy of the cascaded keyword spotter as a function of the operating point of the first stage. The FRR approaches that of the stage 2 model, shown on the first line, as the stage 1 model becomes more lenient. FAR is measured as false alarms per hour on a recording of 924 hours of television background noise. FRR is measured on 65,581 recordings of US English speakers saying a keyword (redacted in anonymized version of paper).

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