

The History of Speech Recognition to the Year 2030

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August 3, 2021

Abstract

The decade from 2010 to 2020 saw remarkable improvements in automatic speech recognition. Many people now use speech recognition on a daily basis, for example to perform voice search queries, send text messages, and interact with voice assistants like Amazon Alexa and Siri by Apple. Before 2010 most people rarely used speech recognition. Given the remarkable changes in the state of speech recognition over the previous decade, what can we expect over the coming decade? I attempt to forecast the state of speech recognition research and applications by the year 2030. While the changes to general speech recognition accuracy will not be as dramatic as in the previous decade, I suggest we have an exciting decade of progress in speech technology ahead of us.

1 Recap

The decade from 2010 to 2020 saw remarkable progress in speech recognition and related technology. Figure 1 is a timeline of some of the major developments in the research, software, and application of speech recognition over the previous decade. The decade saw the launch and spread of phone-based voice assistants like Apple Siri. Far-field devices like Amazon Alexa and Google Home were also released and proliferated.

These technologies were enabled in-part by the remarkable improvement in the word error rates of automatic speech recognition as a result of the rise of deep learning. The key drivers of the success of deep learning in speech recognition have been

- 1) the curation of massive transcribed data sets,
- 2) the rapid rate of progress in graphics processing units, and
- 3) the improvement in the learning algorithms and model architectures.

Thanks to these ingredients, the word error rate of speech recognizers improved consistently and substantially throughout the decade. On two of the most commonly studied benchmarks, automatic speech recognition word error rates have surpassed those of professional transcribers (see figure 3).

This remarkable progress invites the question: what is left for the coming decade to the year 2030? In the following, I attempt to answer this question. But, before I begin, I'd first like to share some observations on the general problem of predicting the future. These findings are inspired by the mathematician (as well as computer scientist and electrical engineer) Richard Hamming, who also happened to be particularly adept at forecasting the future of computing.

2 On Predicting the Future

Richard Hamming in *The Art of Doing Science and Engineering* [10] makes many predictions, many of which have come to pass. Here are a few examples¹

- He stated that by “the year 2020 it would be fairly universal practice for the expert in the field of application to do the actual program preparation rather than have experts in computers (and ignorant of the field of application) do the program preparation.”

¹Quotes and predictions are from chapters 2, 4, and 21 of Hamming [10].

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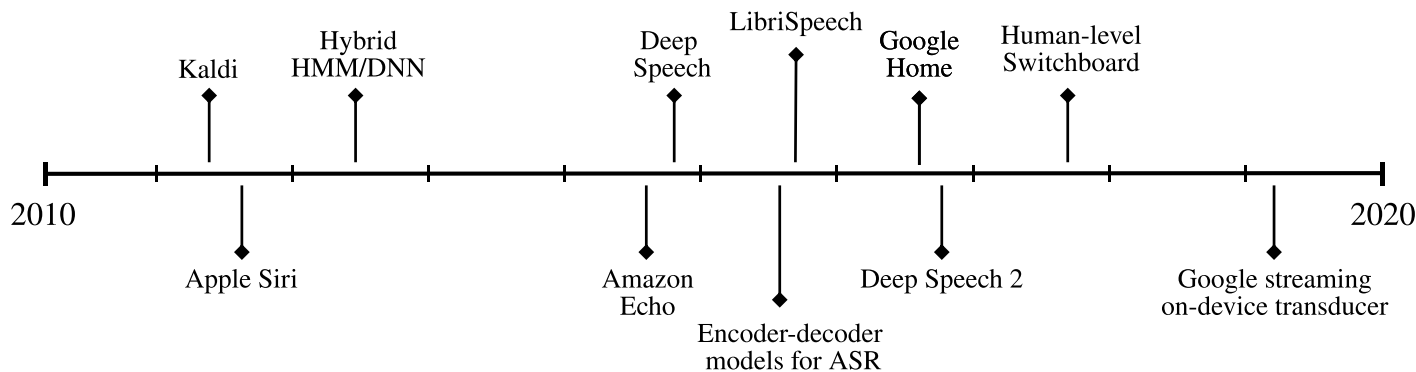


Figure 1: A timeline of some of the major developments in speech recognition from the years 2010 to 2020. The decade saw the launch of voice-based devices and voice assistants, open-source and widely used speech recognition software like Kaldi [23], and larger benchmarks like LibriSpeech [22]. We also saw speech recognition models improve starting from hybrid neural network architectures [15] to more end-to-end models including Deep Speech [11], Deep Speech 2 [2], encoder-decoder models with attention [5], and transducer-based speech recognition [14].

- He predicted that **neural networks** “represent a solution to the programming problem,” and that “they will probably play a large part in the future of computers.”
- He predicted the prevalence of general-purpose rather than special-purpose **hardware**, digital over analog, and high-level programming languages all long before the field had decided one way or another.
- He anticipated the use of fiber-optic cables in place of copper wire for communication well before the switch actually took place.

These are just a few examples of Hamming’s extraordinary prescience. Why was he so good at predicting the future? Here are a few observations which I think were key to his ability:

Practice: One doesn’t get good at predicting the future without actually practicing at it. Hamming practiced. He reserved every Friday afternoon “great thoughts” in which he mused on the future. But he didn’t just predict in isolation. He made his predictions public, which forced him to put them in a communicable form and held him accountable. For example, in 1960 Hamming gave a talk titled “The History of Computing to the Year 2000” (you may recognize the title) in which he predicted how computing would evolve over the

next several decades.

Focus on fundamentals: In some ways, forecasting the future development of technology is just about understanding the present state of technology more than those around you. This requires both depth in one field as well as non-trivial breadth. This also requires the ability to rapidly assimilate new knowledge. Mastering the fundamentals builds a strong foundation for both.

Open mind: Probably the most important trait Hamming exhibited, and in my opinion the most difficult to learn, was his ability to keep an open mind. Keeping an open mind requires constant self-vigilance. Having an open mind one day does not guarantee having it the next. Having an open mind with respect to one scientific field does not guarantee having it with respect to another. Hamming recognized for example that one may be more productive in an office with the door closed, but he kept his office door open as he believed an “open mind leads to the open door, and the open door tends to lead to the open mind” [10, chp. 30].

I’ll add to these a few more thoughts. First, the rate of change of progress in computing and machine learning is increasing. This makes it harder to predict the distant future today than it was 50 or 100 years ago. These days predicting the evolution

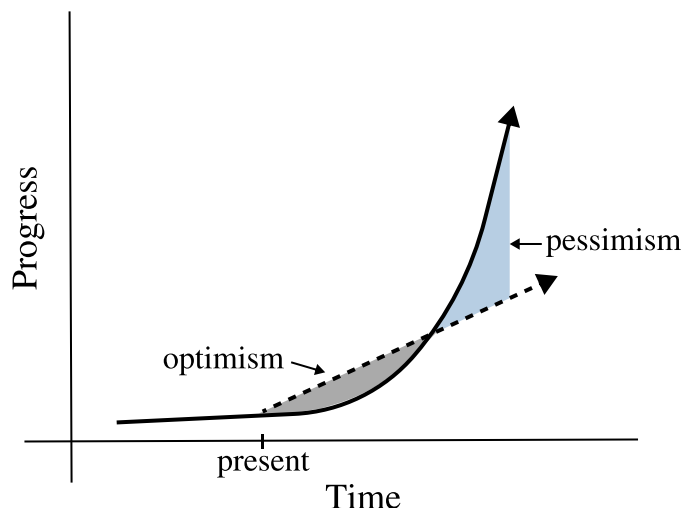


Figure 2: The graph depicts progress as a function of time. The linear extrapolation from the present (dashed line) initially results in overly optimistic predictions. However, eventually the predictions become pessimistic as they are outstripped by the exponential growth (solid line).

of speech recognition even ten years out strikes me as a challenge. Hence my choosing to work with that time frame.

A common saying about technology forecasting is that short-term predictions tend to be overly optimistic and long-term predictions tend to be overly pessimistic. This is often attributed to the fact that progress in technology has been exponential. Figure 2 shows how this happens if we optimistically extrapolate from the present assuming progress is linear with time. Progress in speech recognition over the previous decade (2010-2020) was driven by exponential growth along two key axes. These were compute (e.g. floating-point operations per second) and data set sizes. Whether or not figure 2 applies to speech recognition for the coming decade remains to be seen.

I’m sure a lot of the following predictions will prove wrong. In some ways, particularly when it comes to the more controversial predictions, these are really more of an optimistic wishlist for the future. On that note, let me close this section with the famous words of the computer scientist Alan Kay²:

²Alan Kay is best known for developing the modern

The best way to predict the future is to invent it. sparsity for lighter-weight models
optimization for faster training
effective ways of incorporating prior knowledge for sample efficiency

3 Research Predictions

3.1 Semi-supervised Learning

Prediction: Semi-supervised learning is here to stay. In particular, self-supervised pretrained models will be a part of many machine-learning applications, including speech recognition.

Part of my job as a research scientist is hiring, which means a lot of interviews. I’ve interviewed more than a hundred candidates working on a diverse array of machine-learning applications. Some large fraction, particularly of the natural language applications, rely on a pretrained model as the basis for their machine-learning enabled product or feature. Self-supervised pretraining is already pervasive in language applications in industry. I predict that by 2030 self-supervised pretraining will be just as pervasive in speech recognition.

The past three years of deep learning have been the years of semi and self-supervision. The field has undoubtedly learned how to improve machine-learning models using unannotated data. Self-supervised learning [18] has benefited many of the most challenging machine learning benchmarks. In language tasks, state-of-the-art records have been repeatedly set and surpassed by self-supervised models [6, 24, 33]. Self and semi-supervision are now commonplace and setting records in computer vision [13, 4, 9], abstractive summarization [34] and machine translation [27].

Speech recognition has also benefited from semi-supervised learning. Two approaches are commonly used, both of which work well. The first approach is self-supervised pretraining [26, 35] with a loss function based on contrastive predictive coding [21]. The idea is simple: train the model to predict the future frame(s) of audio given the past. Of course, the devil is in the details and the scale. The

graphical user interface and also object-oriented programming in the Smalltalk programming language.

second approach is **pseudo-labeling** [19, 16, 32]. Again the idea is simple: use the trained model to predict the label on unlabeled data, then train a new model on the predicted labels as if they were the ground truth. And again the devil is in the details and the scale. The fact that pseudo-labeling leads to better models is remarkable. It feels as if we are getting something for nothing, a free lunch. The reason and the regime in which pseudo-labeling works are interesting research questions.

The main challenges with self-supervision are those of scale, and hence accessibility. Right now only the most highly endowed industry research labs (*e.g.* Google Brain, Google DeepMind, Facebook AI Research, OpenAI, *etc.*) have the funds to burn on the compute required to research self-supervision at scale. As a research direction, self-supervision is only becoming less accessible to academia and smaller industry labs.

Research implications: Self-supervised learning would be more accessible given lighter-weight models which could be trained efficiently on less data. Research directions which could lead to this include sparsity for **lighter-weight models**, optimization for faster training, and effective ways of incorporating prior knowledge for sample efficiency.

做出这个判断主要有三点原因：有利于保护用户隐私；端上延时更低；摆脱了对网络的依赖。

3.2 On Device

Prediction: Most speech recognition will happen on the device or at the edge.

There are a few reasons I predict this will happen. First, keeping your data on your device rather than sending it to a central server is more private. The trend towards data privacy will encourage on-device inference whenever possible. If the model needs to learn from a user's data, then the training should happen on the device.

The second reason to prefer on-device inference is latency. In absolute terms, the difference between 10 milliseconds and 100 milliseconds is not much. But the former is well below the perceptual latency of a human, and the latter well above [17, 20]. Google has already demonstrated an on-device speech recognition system with accuracy nearly as

good as a server-side system [14]. The latency differences are easily noticeable.³ From a pragmatic standpoint, the latency of the server-side recognizer is probably sufficient. However, **the imperceptible latency** of the on-device system makes the interaction with the device feel much more responsive and hence more engaging.

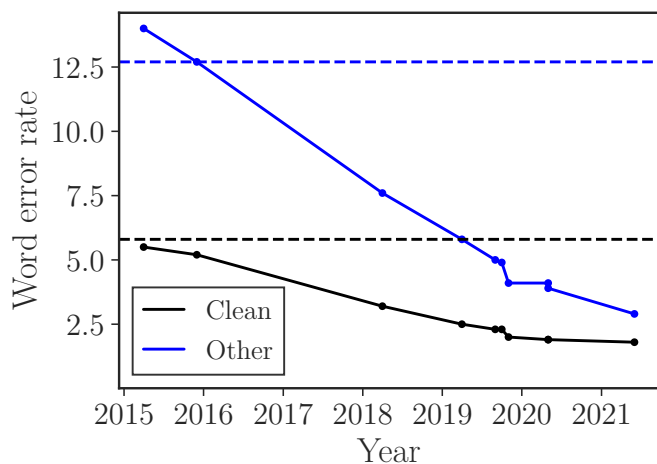
A final reason to prefer on-device inference is 100% availability. Having the recognizer work even without an internet connection or in spotty service means it will work all the time. From a user interaction standpoint there is a big difference between a product which works most of the time and a product which works every time.

Research implications: On-device recognition requires models with smaller compute and memory requirements and which use less energy in order to preserve battery life. Model quantization and knowledge distillation (training a smaller model to mimic the predictions of a more accurate larger model) are two commonly used techniques. Sparsity, which is less commonly used, is another approach to generate lighter-weight models. In sparse models, most of the parameters (*i.e.* connections between hidden states) are zero and can be effectively ignored. Of these three techniques, I think sparsity is the most promising research direction.

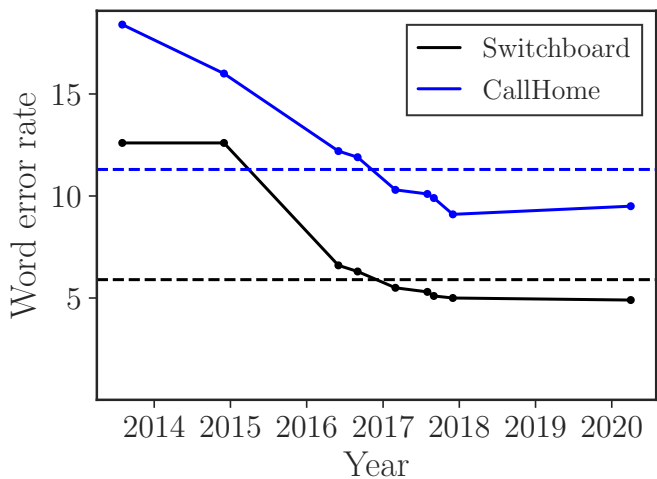
I believe we have extracted most of the value that quantization has to offer. Even in the unlikely best possible scenario of further reducing quantization from 8-bit to 1-bit, we only get a factor-of-eight gain. With distillation, we still have a lot to learn. However, I believe uncovering the mechanism through which distillation works will subsequently enable us to train small models directly rather than taking the circuitous path of training a large model and then a second small model to mimic the large model.

This leaves sparsity as the most promising research direction for lighter-weight models. As findings like the “lottery ticket hypothesis” demonstrate [7], we

³For an example of the perceptual difference in latencies see the blog post on Google's on-device speech recognizer: <https://ai.googleblog.com/2019/03/an-all-neural-on-device-speech.html>



(a) LibriSpeech



(b) Switchboard Hub5'00

Figure 3: The improvement in word error rate over time on the LibriSpeech [22] and Switchboard Hub5'00 benchmarks. The data for these figures is from https://github.com/syhw/wer_are_we. The dashed lines indicate human-level performance. The human-level results on LibriSpeech are reported in Amodei et al. [2], and those on Switchboard are reported in Xiong et al. [31].

have a lot to learn about the role of sparsity in deep learning. In theory, the computational gains from sparsity could be substantial. Realizing these gains will require developments in the software, and possibly hardware, used to evaluate sparse models.

Weak supervision will be an important research direction for on-device training for applications which typically require labeled data. For example, a users interaction with the output of a speech recognizer or the actions they take immediately afterward could be useful signal from which the model can learn in a weakly-supervised manner.

3.3 Word Error Rate

Prediction: By the end of the decade, possibly much sooner, researchers will no longer be publishing papers which amount to “improved word error rate on benchmark X with model architecture Y.”

As you can see in figure 3, word error rates on the two most commonly studied speech recognition benchmarks have saturated. Part of the problem is that we need harder benchmarks for researchers to study. Two recently released benchmarks may spur further research in speech recognition [3, 8]. How-

ever, I predict that these benchmarks will quickly saturate by scaling up models and computation.

Another part of the problem is that we have reached a regime where word error rate improvements on academic benchmarks no longer correlate with practical value. Speech recognition word error rates on both benchmarks in figure 3 surpassed human word error rates several years ago.⁴ However, in most settings humans understand speech better than machines do. This implies that word error rate as a measure of the quality our speech recognition systems does not correlate well with an ability to understand human speech.

A final issue is research in state-of-the-art speech recognition is becoming less accessible as models and data sets are getting larger, and as computing costs are increasing. A few well-funded industry labs are rapidly becoming the only places that can afford this type of research. As the advances become more incremental and further from academia,

⁴Estimates of human-level word error rates on the CallHome portion of Hub5'00 vary considerably. For example Saon et al. [25] report a best result 6.8 out of three transcribers whose results vary by nearly 2.0 absolute word error rate.

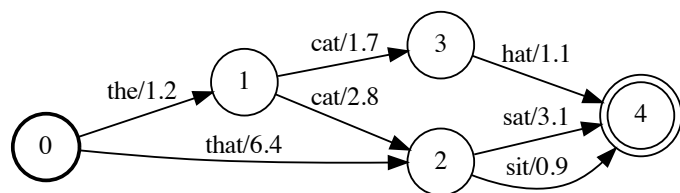


Figure 4: An example lattice used to encode multiple hypotheses output from a speech recognizer with differing weights.

this part of the field will continue to shift from research labs to engineering organizations.

3.4 Richer Representations

Prediction: Transcriptions will be replaced by richer representations for downstream tasks which rely on the output of a speech recognizer. Examples of such downstream applications include conversational agents, voice-based search queries, and digital assistants.

Downstream applications often don’t care about a verbatim transcription; they care about semantic correctness. Hence, improving the word error rate of a speech recognizer often does not improve the objective of the downstream task. One possibility is to develop a *semantic error rate* and use it to measure the quality of the speech recognizer. This is a challenging albeit interesting research problem.

I think a more likely outcome is to give downstream applications richer representations from the speech recognizer. For example, instead of passing a single transcription, passing a lattice of possibilities (as in figure 4) which captures the uncertainty for each could be much more useful.

Research implications: The exact structure used to encode the representation is an open question. One possibility could be some sort of weighted transducer which if differentiable could allow for fine-tuning the recognizer to specific applications [1, 12]. This type of representation also requires models which are able to ingest variable-sized graphs as input.

3.5 Personalization

Prediction: By the end of the decade, speech recognition models will be deeply personalized to individual users.

One of the main distinctions between the automatic recognition of speech and the human interpretation of speech is in the use of context. Humans rely on a lot of context when speaking to one another. This context includes the topic of conversation, what was said in the past, the noise background, and visual cues like lip movement and facial expressions. We have, or will soon reach, the Bayes error rate for speech recognition on short (*i.e.* less than ten second long) utterances taken out of context. Our models are using the signal available in the data to the best of their ability. To continue to improve the machine understanding of human speech will require leveraging context as a deeper part of the recognition process.

One way to do this is with personalization. Personalization is already used to improve the recognition of utterances of the form “call <NAME>”. Sim et al. [29] found personalizing a model with a user’s contact list improves named entity recall from 2.4% to 73.5% – a massive improvement. Personalizing models to individual users with speech disorders improves word error rates by 64% relative [30]. Personalization can make a huge difference in the quality of the recognition, particularly for groups or domains that are underrepresented in the training data. I predict we will see much more pervasive personalization by the end of the decade.

Research implications: On-device personalization requires on-device training which in itself requires lighter-weight models and some form of weak supervision (see section 3.2). Personalization requires models which can be easily customized to a given user or context. The best way to incorporate such context into a model is still a research question.

因为当语音识别系统优化到一定程度，下游任务有可能会对WER不再敏感，这时候可能需要定义新的指标来衡量识别系统的改进，比如 semantic error rate (这点也是深有感触)。这时候识别系统的输出换成 lattice 等更丰富的信息表征，可能对下游任务帮助更大。作者预测到2030年，语音识别系统具备一定的个性化能力。

作者 argue 说人在理解语音的时候会结合上下文的能力，比如当前对话的主题、过去说的内容、说话人的习惯等等，这些信息对于理解语音很有帮助。

Table 1: Predictions for the progress in speech recognition research and applications by the year 2030.

Prediction
Self-supervised learning and pretrained models are here to stay.
Most speech recognition (inference) will happen at the edge.
On-device model training will be much more common.
Sparsity will be a key research direction to enable on-device inference and training.
Improving word error rate on common benchmarks will fizzle out as a research goal.
Speech recognizers will output richer representations (graphs) for use by downstream tasks.
Personalized models will be commonplace.
Most transcription services will be automated.
Voice assistants will continue to improve, but incrementally.

4 Application Predictions

4.1 Transcription Services

Prediction: By the end of the decade, 99% of transcribed speech services will be done by automatic speech recognition. Human transcribers will perform quality control and correct or transcribe the more difficult utterances. Transcription services include, for example, captioning video, transcribing interviews, and transcribing lectures or speeches.

4.2 Voice Assistants

Prediction: Voice assistants will get better, but incrementally, not fundamentally. Speech recognition is no longer the bottleneck to better voice assistants. The bottlenecks are now fully in the language understanding domain including the ability to maintain conversations, multi-ply contextual responses, and much wider domain question and answering. We will continue to make incremental progress on these so-called AI-complete problems,⁵ but I don’t expect them to be solved by 2030.

Will we live in smart homes that are always listening and can respond to our every vocal beck and call? No. Will we wear augmented reality glasses

on our faces and control them with our voice? Not by 2030.

5 Conclusion

Table 1 summarizes my predictions for the progress in speech recognition to the year 2030. The predictions show that the coming decade could be just as exciting and important to the development of speech recognition and spoken language understanding as the previous one. We still have many research problems to solve before speech recognition will reach the point where it works all the time, for everyone. However, this is a goal worth working toward, as speech recognition is a key component to more fluid, natural, and accessible interactions with technology.

Acknowledgements

Thanks to Chris Lengerich, Marya Hannun, Sam Cooper, and Yusuf Hannun for their feedback on this article.

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⁵Shapiro [28, sec. 4] defines an AI task as AI-complete if solving it is equivalent to “solving the general AI problem”, which he defines as “producing a generally intelligent computer program”.

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