Google Search by Voice: A case study

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1 Introduction

Using our voice to access information has been part of science fiction ever since the days of Captain Kirk talking to the Star Trek computer. Today, with powerful smartphones and cloud based computing, science fiction is becoming reality. In this chapter we give an overview of Google Search by Voice and our efforts to make speech input on mobile devices truly ubiquitous.

The explosion in recent years of mobile devices, especially web-enabled smartphones, has resulted in new user expectations and needs. Some of these new expectations are about the nature of the services - e.g., new types of up-to-the-minute information (”where’s the closest parking spot?”) or communications (e.g., ”update my facebook status to ’seeking chocolate’”). There is also the growing expectation of ubiquitous availability. Users increasingly expect to have constant access to the information and services of the web. Given the nature of delivery devices (e.g., fit in your pocket or in your ear) and the increased range of usage scenarios (while driving, biking, walking down the street), speech technology has taken on new importance in accommodating user needs for ubiquitous mobile access - any time, any place, any usage scenario, as part of any type of activity.

A goal at Google is to make spoken access ubiquitously available. We would like to let the user choose - they should be able to take it for granted that spoken interaction is always an option. Achieving ubiquity requires two things: *availability* (i.e., built into every possible interaction where speech input or output can make sense), and *performance* (i.e., works so well that the modality adds no friction to the interaction).

This chapter is a case study of the development of Google Search by

Voice - a step toward our long term vision of ubiquitous access. While the integration of speech input into Google search is a significant step toward more ubiquitous access, it posed many problems in terms of the performance of core speech technologies and the design of effective user interfaces. Work is ongoing - the problems are far from solved. However, we have, at least, achieved a level of performance such that usage is growing rapidly, and many users become repeat users.

In this chapter we will present the research, development, and testing of a number of aspects of speech technology and user interface approaches that have helped improve performance and/or shed light on issues that will guide future research. There are two themes which underlie much of the technical approach we are taking: *delivery from the cloud* and *operating at large scale.*

Delivery from the cloud: Delivery of services from the cloud enables a number of advantages when developing new services and new technologies. In general, research and development at Google is conducted "in-vivo" — as part of actual services. This way, we benefit from an ongoing flow of real usage data. That data is valuable for guiding our research in the directions of most value to end-users, and supplying a steady flow of data for training systems. Given the statistical nature of modern speech recognition systems, this ongoing flow of data for training and testing is critical. Much of the work described below, including core technology development, user interface development, and user studies, depends critically on constant access to data from real usage.

Operating at scale: Mobile voice search is a challenging problem for many reasons - for example, vocabularies are huge, input is unpredictable, and noise conditions may vary tremendously due to the wide-ranging usage scenarios while mobile. Additionally, well known issues from earlier deployments of speech technology, such as dealing with dialectal variations, are compounded by the large scale nature of voice search.

Our thesis in handling these issues is that we can take advantage of the large amount of compute power, a rapidly growing volume of data, and the infrastructure available at Google to process more data and model more conditions than ever done before in the history of speech recognition. Therefore, many of the techniques and research directions described below are focussed on building models at scale - i.e., models that can take advantage of huge amounts of data and the compute power to train and run them. Some of the approaches discussed will be methods for exploiting large amounts of data - for example with "unsupervised learning", i.e., the ability to train models on all the data that comes in, without the need for human intervention for transcription or labeling. Another key set of issues involve the question of how to "grow" models as more data becomes available. In other words, given much more data, we can train richer models that better capture the complexities of speech. However, there remain many open questions about the most effective ways to do so.

In addition to taking advantage of the cloud and our ability to operate at large scale, we also take advantage of other recent technology advances. The maturing of powerful search engines provides a very effective way to give users what they want if we can recognize the words of a query. The recent emergence of widely-used multi-modal platforms (smartphones) provides both a powerful user interface capability and a delivery channel.

This chapter presents the approaches we have taken to deliver and optimize the performance of spoken search, both from the point of view of core technology and user interface design. In Section 2 we briefly describe the history of search by voice efforts at Google. Section 3 provides an in depth description of the technology employed at Google and the challenges we faced to make search by voice a reality. In Section 4 we explore the user interface design issues. Multi-modal interfaces, combining speech and graphical elements, are very new, and there are many challenges to contend with as well as opportunities to exploit. Finally, in Section 5 we describe user studies based on our deployed applications.

2 History

2.1 GOOG-411

Searching for information by voice has been part of our every day lives since long before the internet became prevalent. It was already the case thirty years ago that, if you needed information for a local business, the common approach was to dial directory assistance (411 in the US) and ask an operator for the telephone number.

800-GOOG-411 [2] is an automated system that uses speech recognition and web search to help people find and call businesses. Initially this system followed the well known model of first prompting the user for the "city and state" followed by the desired business listing as depicted in Figure 1.

This basic dialog has been ingrained in our minds since long before interactive voice response systems (IVR) replaced all or part of the live operator interaction.

Pre-IVR systems use "store-and-forward" technology that records the "city-and-state" the caller is requesting and then plays the city and state to

GOOG411:	Calls recorded... Google! What city and state?
Caller:	*Palo Alto, California*
GOOG411:	What listing?
Caller:	*Patxis Chicago Pizza*
GOOG411:	Patxis Chicago Pizza, on Emerson Street. I'll connect you...

Figure 1: Early dialog for a GOOG-411 query.

the operator. This frees the operator from direct interaction with the user and results in substantial savings of human labor. Additionally, it constrains the search for businesses to the chosen city.

In 2008 we deployed a new version of GOOG-411 which allowed (and encouraged) the user to state their need in a single utterance rather than in sequential utterances that split apart the location and the business (Figure 2). This was motivated by our desire to accommodate faster interactions as well as allow the user greater flexibility in how they describe their needs. This approach introduces new speech recognition challenges, given that we can no longer constrain the business listing language model to only those businesses in or near the chosen city. In [10] we investigated the effect of moving from a city conditional to nation wide language model that allows recognition of the business listing as well as the location in a single user response.

GOOG411:	Calls recorded... Google! Say the business, and the city and state.
Caller:	*Patxis Chicago Pizza in Palo Alto.*
GOOG411:	Patxis Chicago Pizza, on Emerson Street. I'll connect you...

Figure 2: Single shot dialog for a GOOG-411 query.

Moving from a two-step to a single-step dialog allowed for faster and arguably more natural user interactions. This, however, came at the price of increased recognition complexity, for the reasons described above. This was our first step moving from traditional directory assistance to more complex systems. The next step was to exploit new modalities.

2.2 Google Maps for Mobile (GMM)

Traditional directory assistance applications are limited to a single modality, using voice as both input and output. With the advent of smartphones with large screens and data connectivity, we could move to a multi-modal user interface with speech or text as the input modality, and maps with superimposed business listings as the output modality.

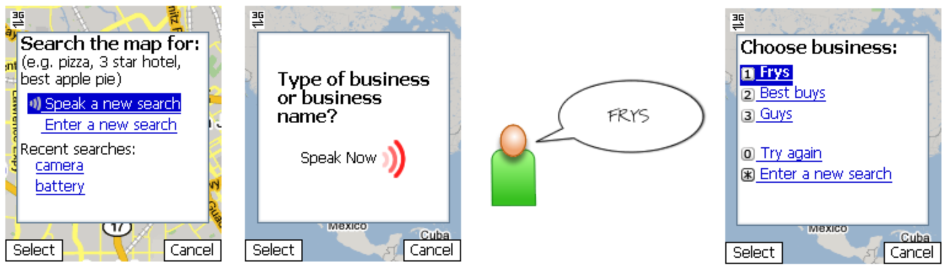


Figure 3: Google Maps for Mobile, with voice interface.

In March 2008 we introduced our first multi-modal speech application for Google Maps for Mobile (GMM). Figure 3 depicts a multi-modal interface for directory assistance that we built on top of GMM.

A multi-modal experience has some distinct advantages compared to the IVR (voice-only) system. First, the output modality can be visual rather than spoken, allowing much richer information flow. Google Maps for Mobile can show the location of the business and other related information directly on a map. The contact information, address, and any other meta information about the business (such as ratings) can easily be displayed. A second major advantage relates to the time it takes the user to both search for and digest information. Due to the multi-modality of the search experience, the total time spent is significantly less than the single input/output spoken modality of the IVR system. Finally, the cognitive load on the user is greatly reduced - the ephemeral nature of speech places significant cognitive demands on a user when the information communicated is lengthy or complex. These advantages enable a substantial improvement in the quality of interaction and quality of information one can provide compared to traditional IVR systems.

2.3 Google Search by Voice

Mobile web search is a rapidly growing area of interest. Internet-enabled smartphones account for an increasing share of the mobile devices sold throughout the world, and most models offer a web browsing experience that rivals desktop computers in display quality. Users are increasingly turning to their mobile devices when doing web searches, driving efforts to enhance the usability of web search on these devices.

Although mobile device usability has improved, typing search queries can still be cumbersome, error-prone, and even dangerous in some usage scenarios.

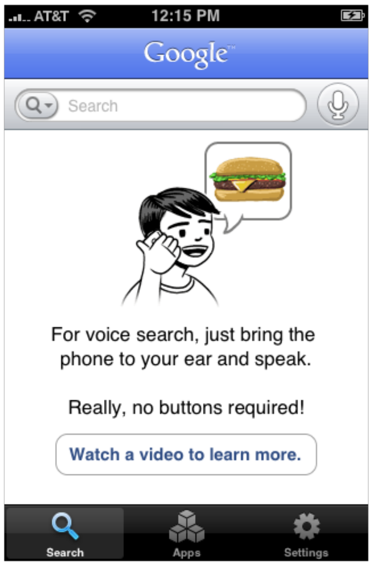

AT&T
12:15 PM
Google
Search
For voice search, just bring the phone to your ear and speak.
Really, no buttons required!
Watch a video to learn more.
Search
Apps
Settings

Figure 4: Google search by Voice for iPhone.

In November 2008 we introduced Google Mobile App (GMA) for iPhone (Figure 4) that included a search by voice feature. GMA search by voice extended the paradigm of multi-modal voice search from searching for businesses on maps to searching the entire world wide web. In the next few sections we discuss the technology behind these efforts and some lessons we have learned by analyzing data from our users.

3 Technology

The goal of Google search by Voice is to recognize any spoken search query. Table 1 lists some example queries, hinting at the great diversity of inputs we must accommodate. Unlike GOOG-411, which is very domain-dependent, Google search by Voice must be capable of handling anything that Google search can handle. This makes it a considerably more challenging recognition problem, because the vocabulary and complexity of the queries is so large (more on this later in the language modeling Section 3.4).

Figure 5 depicts the basic system architecture of the recognizer behind

Example Query
images of the grand canyon
what's the average weight of a rhinoceros
map of san francisco
what time is it in bangalore
weather scarsdale new york
bank of america dot com
A T and T
eighty one walker road
videos of obama state of the union address
genetics of color blindness

Table 1: Example queries to Google search by Voice.

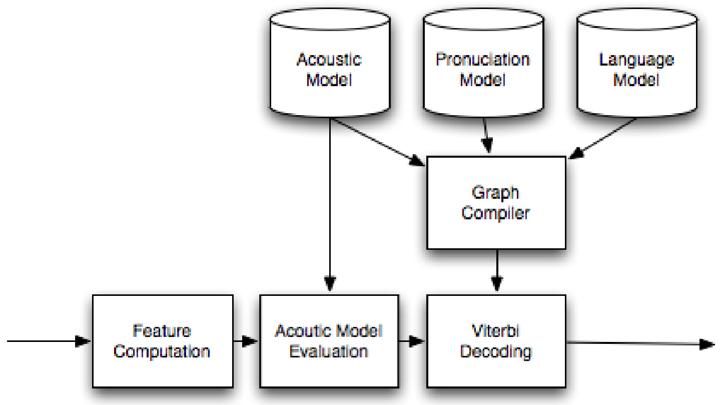


Figure 5: Basic block diagram of a speech recognizer.

Google search by Voice. For each key area of acoustic modeling and language modeling we will describe some of the challenges we faced as well as some of the solutions we have developed to address those unique challenges.

In Section 3.1 we will review some of the common metrics we use to evaluate the quality of the recognizer. In Sections 3.2, 3.3, 3.4, we describe the algorithms and technologies used to build the recognizer for Google search by Voice.

3.1 Metrics

Choosing appropriate metrics to track the quality of the system is critical to success. The metrics drive our research directions as well as provide insight and guidance for solving specific problems and tuning system performance. We strive to find metrics that illuminate the end-user experience, to make sure that we optimize the most important aspects and make effective tradeoffs. We also design metrics which can bring to light specific issues with the underlying technology. The metrics we use include:

1. Word Error Rate (WER):

   The word error rate measures misrecognitions at the word level: it compares the words outputted by the recognizer to those the user really spoke. Every error (substitution, insertion or deletion) is counted against the recognizer.

$$WER = \frac{\text{Number of Substitution + Insertions + Deletions}}{\text{Total number of words}}$$

2. Semantic Quality (WebScore):

   For Google search by Voice, individual word errors do not necessarily effect the final search results shown. For example, deleting function words like "in" or "of" generally do not change the search results. Similarly, misrecognition of the plural form of a word (missing "s") would also not generally change the search results.

   We therefore track the semantic quality of the recognizer (WebScore) by measuring how many times the search result as queried by the recognition hypothesis varies from the search result as queried by a human transcription.

$$WebScore = \frac{\text{Number of correct search results}}{\text{Total number of spoken queries}}$$

   A better recognizer has a higher WebScore. The WebScore gives us a much clearer picture of what the user experiences when they search by voice. In all our research we tend to focus on optimizing this metric, rather than the more traditional WER metric defined above.

3. Perplexity (PPL):

Perplexity is, crudely speaking, a measure of the size of the set of words that can be recognized next, given the previously recognized words in the query.

This gives us a rough measure of the quality of the language model. The lower the perplexity, the better the model is at predicting the next word.

$$PPL = 2^{\sum_{i=1}^{N} \frac{1}{N} \log_2 q(x_i)}$$

4. Out-of-Vocabulary (OOV) Rate:

   The out-of-vocabulary rate tracks the percentage of words spoken by the user that are not modeled by our language model. It is important to keep this number as low as possible. Any word spoken by our users that is not in our vocabulary will ultimately result in a recognition error. Furthermore, these recognition errors may also cause errors in surrounding words due to the subsequent poor predictions of the language model and acoustic misalignments.

5. Latency:

   Latency is defined as the total time (in seconds) it takes to complete a search request by voice. More precisely, we define latency as the time from when the user finishes speaking until the search results appear on the screen. Many factors contribute to latency as perceived by the user: (a) the time it takes the system to detect end-of-speech, (b) the total time to recognize the spoken query, (c) the time to perform the web query, (d) the time to return the web search results back to the client over the network, and (e) the time it takes to render the search results in the browser of the users phone. Each of these factors are studied and optimized to provide a streamlined user experience.

3.2 Acoustic Modeling

Acoustic models provide an estimate for the likelihood of the observed features in a frame of speech given a particular phonetic context. The features are typically related to measurements of the spectral characteristics of a time-slice of speech. While individual recipes for training acoustic models vary in their structure and sequencing, the basic process involves aligning transcribed speech to states within an existing acoustic model, accumulating frames associated with each state, and re-estimating the probability distributions associated with the state, given the features observed in those frames. The details of these systems are extensive, but improving models typically includes getting training data that's strongly matched to the particular task and growing the numbers of parameters in the models to better characterize the observed distributions. Larger amounts of training data allow more parameters to be reliably estimated.

There are two levels of bootstrapping required. Once a starting corpus is collected, there are bootstrap training techniques to grow acoustic models starting with very simple models (i.e., single-Gaussian context-independent systems). But there is another bootstrapping problem at the level of the application definition. In order to collect 'real data' matched to users actually interacting with the system, we need an initial system with acoustic and language models. For Google search by Voice, we used GOOG-411 acoustic models together with a language model estimated from web query data. There is a balance to maintain in which the application needs to be compelling enough to attract users, but not so challenging from a recognition perspective that it makes too many errors and is no longer useful. Google makes it easy to push the boundaries of what might be possible while engaging as many users as possible - partly due to the fact that delivering services from the cloud enables us to rapidly iterate and release improved versions of systems.

Once we fielded the initial system, we started collecting data for training and testing. For labeling we have two choices: supervised labeling where we pay human transcribers to write what is heard in the utterances, and unsupervised labeling where we rely on confidence metrics from the recognizer and other parts of the system together with the actions of the user to select utterances which we think the recognition result was likely to be correct. We started with supervised learning, aggressively transcribing data for training, and then migrated toward unsupervised learning as the traffic increased.

3.2.1 Accuracy of an Evolving System

The basic form of the acoustic models used are common in the literature. The experiments shown here all use 39-dimensional PLP-cepstral [5] coefficients together with online cepstral normalization, LDA (stacking 9 frames), and STC [3]. The acoustic models are triphone systems grown from decision trees, and use GMMs with variable numbers of Gaussians per acoustic state. We optimize ML, MMI, and 'boosted'-MMI [8] objective functions in training.

Figure 6 shows the accuracy of the system on an off-line test set across various acoustic models developed in the first year of production. Each point on the x-axis represents a different acoustic model. These evaluations all use the same production language model (LM) estimated toward the end of the first year of deployment, but change the underlying acoustic model. The test set has 14K utterances and 46K words. The metric used here is WebScore, described above, which provides a measure of sentence-level semantic accuracy.

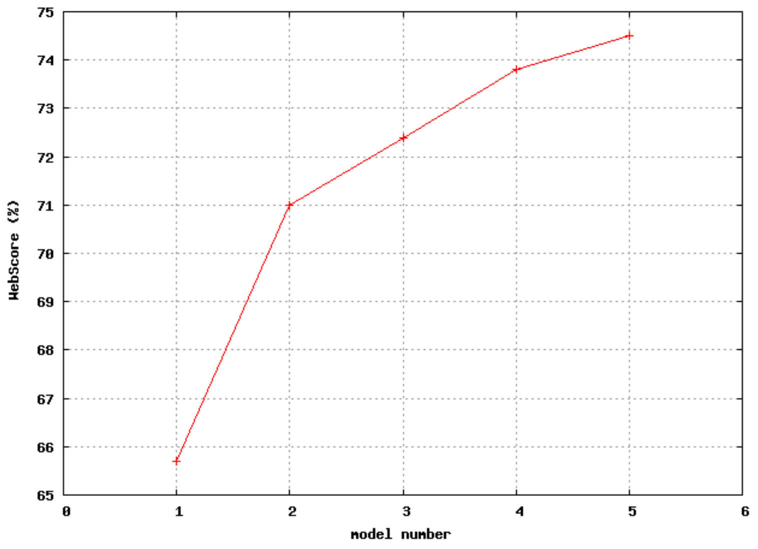


Figure 6: WebScore evolution over time.

The first point on the graph shows the baseline performance of the system with mismatched GOOG-411 acoustic models. The second point, model 2, largely shows the impact of matching the acoustic models to the task using around 1K hours of transcribed data. For model 3, we doubled the training data and changed our models to use a variable number of Gaussians for each state. Model 4 includes boosted-MMI and adds around 5K hours of unsupervised data. Model 5 includes more supervised and unsupervised data, but this time sampled at 16KHz.

Potential bugs in experiments make learning from negative results sketchy in speech recognition. When some technique doesn't improve things there's always the question of whether the implementation was wrong. Despite that, from our collection of positive and negative experiments we've seen a few general trends. The first is the expected result that adding more data helps, especially if we can keep increasing the model size. This is the basic engineering challenge in the field. We're also seeing that most of the wins come from optimizations close to the final training stages. Particularly, once we moved to 'elastic models' that use different numbers of Gaussians for different acoustic states (based on the number of frames of data aligned with the state), we saw very little change with wide-ranging differences in decision tree structure. Similarly, with reasonably well-defined final models, optimizations of LDA and CI modeling stages have not led to obvious wins with the final models. Finally, our systems currently see a mix of 16 kHz and 8 kHz data. While we've seen improvements from modeling 16 kHz data directly (compared to modeling only the lower frequencies of the same 16 kHz data), so far we do better on both 16 kHz and 8 kHz tests by mixing all of our data and only using spectra from the first 4 kHz of the 16 kHz data. We expect this result to change as more traffic migrates to 16 kHz.

3.2.2 Next Challenges

The growing user base of voice search together with Google's computational infrastructure provides a great opportunity to scale our acoustic models. The inter-related challenges include how and where to add acoustic parameters, what objective functions to optimize during training, how to find the optimal acoustic modeling size for a given amount of data, how to field a realtime service with increasingly large acoustic models, and how to get reliable labels for exponentially increasing amounts of data. Early experiments in these directions suggest that the optimal model size is linked to the objective function: the best MMI models may come from ML models that are smaller than the best ML models; that MMI objective functions may scale well with increasing unsupervised data; that speaker clustering techniques may show promise for exploiting increasing amounts of data; and that combinations of multi-core decoding, optimizations of Gaussian selection in acoustic scoring, and multi-pass recognition provide suitable paths for increasing the scale of acoustic models in realtime systems.

3.3 Text Normalization

We use written queries to google.com in order to bootstrap our language model for Google search by Voice. The large pool of available queries allows us to create rich models. However, we must transform written form into spoken form prior to training. This section discusses our approach to text normalization, i.e., the approach by which we perform that transformation.

Written queries contain a fair number of cases which require special attention to convert to spoken form. Analyzing the top million vocabulary items before text normalization we see approximately 20% URLs and 20+% numeric items in the query stream. Without careful attention to text normalization the vocabulary of the system will grow substantially.

We adopt a finite state [1] approach to text normalization. Let $T(\text{written})$ be an acceptor that represents the written query. Conceptually the spoken form is computed as follows

$$T(\text{spoken}) = \text{bestpath}(T(\text{written}) \circ N(\text{spoken}))$$

where $N(\text{spoken})$ represents the transduction from written to spoken form. Note that composition with $N(\text{spoken})$ might introduce multiple alternate spoken representations of the input text. For the purpose of computing n-grams for spoken language modeling of queries we use the 'bestpath' operation to select a single most likely interpretation.

3.3.1 Text Normalization transducers

The text normalization is run in multiple phases. Figure 7 depicts the text normalization process.

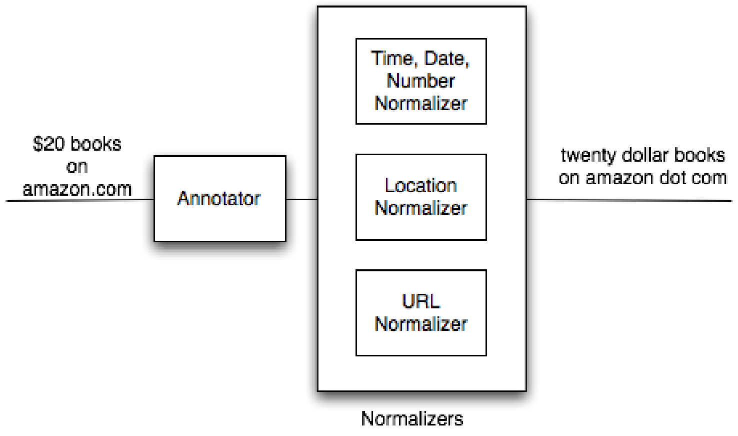


Figure 7: Category/Context specific text normalization.

In the first step we annotate the data. In this phase we classify parts (sub strings) of queries into a set of known categories (e.g time, date, url, location).

Once the query is annotated, it is possible to perform context-aware normalization on the substrings. Each category has a corresponding text normalization transducer $N_{\text{cat}}(\text{spoken})$ that is used to normalize the substring. Depending on the category we either use rule based approaches or a statistical approach to construct the text normalization transducer.

For numeric categories like date, time, and numbers it is easy enough to describe $N(\textit{spoken})$ using context dependent rewrite rules.

The large number of URLs contained in web queries poses some challenging problems. There is an interesting intersection between text normalization of URL queries and segmentation of text for languages like Japanese and Mandarin Chinese. Both require segmenting the text into its corresponding word constituents [9]. For example, one reads the URL `cancercentersofamerica.com` as "cancer centers of america dot com". For the URL normalizer $N_{\text{url}}(\text{spoken})$ we train a statistical word decompounder that segments the string.

3.4 Large Scale Language Modeling

In recent years language modeling has witnessed a shift from advances in core modeling techniques (in particular, various n-gram smoothing algorithms) to a focus on scalability. The main driver behind this shift is the availability of significantly larger amounts of training data that are relevant to automatic speech recognition problems.

In the following section we describe a series of experiments primarily designed to understand the properties of scale and how that relates to building a language model for modeling spoken queries to `google.com`. A typical Voice Search language model is trained on over 230 billion words. The size of this data set presents unique challenges as well as new opportunities for improved language modeling.

Ideally one would build a language model on spoken queries. As mentioned above, to bootstrap we start from written queries (typed) to `google.com`. After text normalization we select the top 1 million words. This results in an out-of-vocabulary (OOV) rate of 0.57%. Table 2 depicts the performance of the language model on unseen query data (10K) when using Katz smoothing [7].

The first language model (LM) which has approximately 15 million n-grams is used for constructing the first pass recognition network. Note this language model requires aggressive pruning (to about 0.1% of its unpruned size). The perplexity hit taken by pruning the LM is significant - 50%

Order	no. n-grams	pruning	PPL	n-gram hit-ratios
3	15M	entropy (Stolcke)	190	47/93/100
3	7.7B	none	132	97/99/100
5	12.7B	cut-off (1-1-2-2-2)	108	77/88/97/99/100

Table 2: Typical Google Voicesearch LM, Katz smoothing: the LM is trained on 230 billion words using a vocabulary of 1 million words, achieving out-of-vocabulary rate of 0.57% on test data.

relative. Similarly, the 3-gram hit ratio is halved.

The question we wanted to ask is how does the size of the language model effect the performance of the system. Are these huge numbers of n-grams that we derive from the query data important?

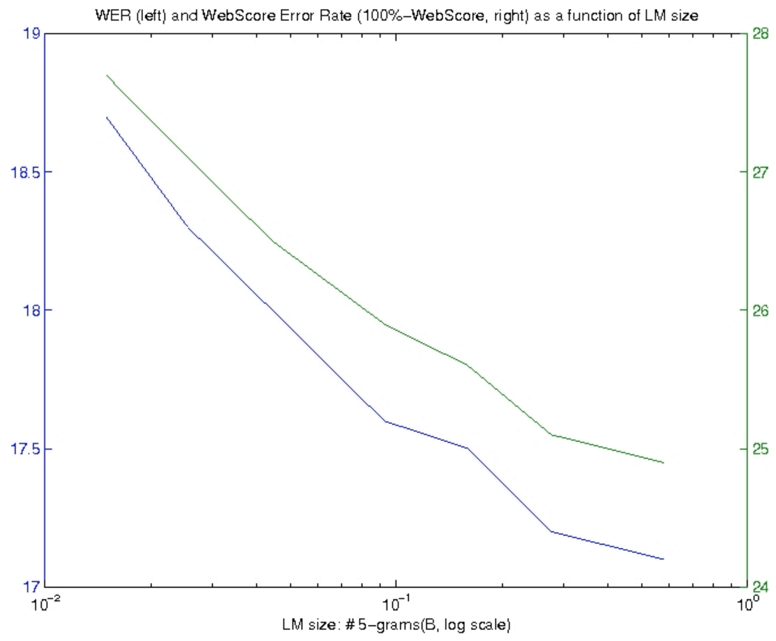


Figure 8: Word Error (WER) and WebScore as a function of language model size.

Figure 8 depicts the WER and WebScore for a series of language models increasing in size from 15 million n-grams up to 2 billion n-grams. As the size of the language model increases we see a substantial reduction in both the word error rate and associated WebScore [4].

Figure 9: Word Error Rate (WER) and Perplexity as a function of language model size.

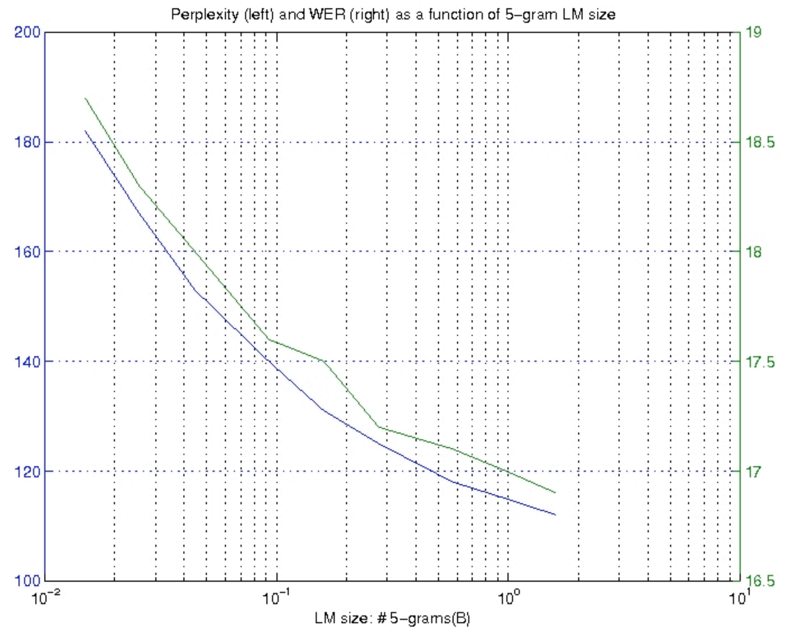


Figure 9 depicts the WER and the Perplexity for the same set of language models. We find a strong correlation between the perplexity of the language model and the word error rate. In general perplexity has been a poor predictor of the corresponding word error, so this results was rather surprising.

3.4.1 Locale Matters

We ran some experiments to examine the effect of locale on language model quality. We built locale specific English language models using training data from prior to September 2008 across 3 English locales: USA, Britain, and Australia. The test data consisted of 10k queries for each locale sampled randomly from Sept-Dec 2008.

Tables 3, 4 and 5 show the results. The dependence on locale is surprisingly strong: using an LM on out-of-locale test data doubles the OOV rate and perplexity.

We have also build a `combined` model by pooling all data, with the results shown on the last row of Table 5.

Combining the data negatively impacts all locales. The farther the locale

Training	Test Locale		
Locale	`USA`	`GBR`	`AUS`
`USA`	**0.7**	1.3	1.6
`GBR`	1.3	**0.7**	1.3
`AUS`	1.3	1.1	**0.7**

Table 3: Out of Vocabulary Rate: locale specific vocabulary halves the OoV rate

Training	Test Locale		
Locale	`USA`	`GBR`	`AUS`
`USA`	**132**	234	251
`GBR`	260	**110**	224
`AUS`	276	210	**124**

Table 4: Perplexity of unpruned LM: locale specific LM halves the PPL of the unpruned LM

from `USA` (as seen on the first line, `GBR` is closer to `USA` than `AUS`), the more negative the impact of clumping all the data together, relative to using only the data from that given locale.

Training	Test Locale		
Locale	`USA`	`GBR`	`AUS`
`USA`	**210**	369	412
`GBR`	442	**150**	342
`AUS`	422	293	**171**
`combined`	227	210	271

Table 5: Perplexity of pruned LM: locale specific LM halves the PPL of the unpruned LM. Pooling all data is suboptimal.

In summary, we find that locale-matched training data resulted in higher quality language models for the three English locales tested.

4 User Interface

"Multi-modal" features, like Google Search by Voice, provide a highly flexible and data-rich alternative to the voice-only telephone applications that preceded them. After all, they take advantage of the best aspects of both speech and graphical modalities. However, despite their benefits, multi-modal applications represent largely uncharted territory in terms of user interface design. Consequently, there are many aspects that will need refinement or redesign. The good news is that, as more user data is gathered, we are gaining a much better understanding of the issues. What's more, as more designers and developers try their hand at this type of interface this knowledge will grow even faster. In this section, we describe just a few of the unique characteristics that make multi-modal applications both appealing to users as well as challenging for designers. For some of these challenges, we present viable solutions based on user data. For others, we describe ongoing experimentation that will ultimately lead to a better user experience.

4.1 Advantages of Multi-Modal User Interfaces

4.1.1 Spoken Input vs. Output

While speech is both convenient and effective as an input method, especially as an alternative to typing on tiny mobile keyboards, spoken output is very limited given its sequential nature. Consider the following examples from GOOG-411. The first involves a search for a specific restaurant named "Patxi's Chicago Pizza" while the second shows a search for a common restaurant category, namely "pizza".

GOOG411:	Calls recorded... Google! Say the business and the city and state.
Caller:	*Patxi's Chicago Pizza in Palo Alto.*
GOOG411:	Patxi's Chicago Pizza, on Emerson Street. I'll connect you...

Figure 10: Specific business search with GOOG-411.

As shown in Figure 10, GOOG-411 handles specific name queries very efficiently, quickly connecting the caller to the business usually in about 30 seconds. However, when a caller specifies the business category as opposed to a specific name, as in Figure 11, it takes more than a minute just to hear the first set of choices. If the caller chooses to further "browse" the list and perhaps listen to the details of one or two choices, the call time will be doubled. If it goes this far, however, there is a good chance the user

GOOG411:	Calls recorded... Google! Say the business and the city and state.
Caller:	*Pizza in Palo Alto.*
GOOG411:	Pizza in Palo Alto... Top eight results:
	Number 1: Patxi's Chicago Pizza, on Emerson Street
	To select number one, press 1 or say "number one".
	Number 2: Pizza My Heart, on University Avenue.
	Number 3: Pizza Chicago, on El Camino Real.
	[...]
	Number 8: Spot a Pizza Place: Alma-Hamilton, on Hamilton Avenue

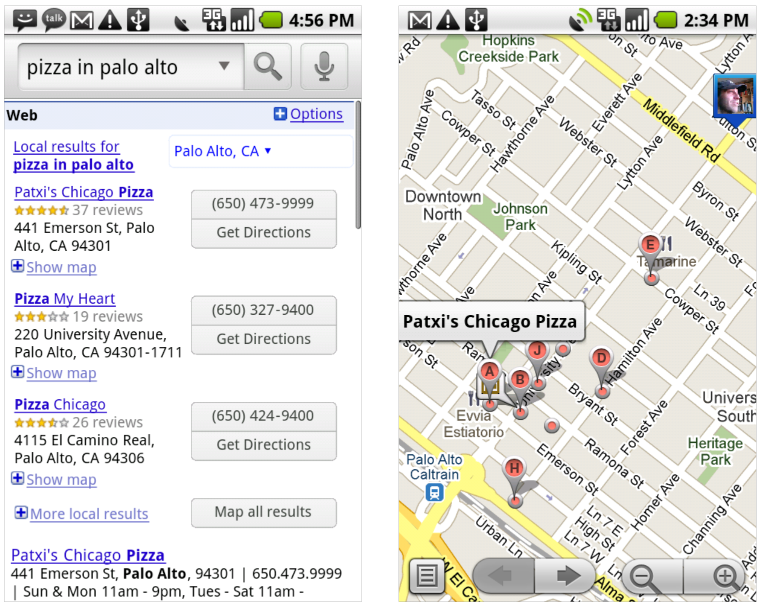
Figure 11: Business category search with GOOG-411.

will hang up without making a selection. It takes a great deal of time and concentration to process spoken information, and most user's pain threshold is fairly low. While not conclusive, the GOOG-411 data supports this, as specific business name queries outnumber category searches more than five to one.

4.1.2 A Picture Paints a Thousand Words

Now consider the screens in Figure 12 which show the results displayed for the same "Pizza in Palo Alto" query using Google's voice search feature on Android. Not only does the user receive more information, but the graphical display allows much of it to be processed in parallel, saving a great deal of time.

The screen on the left shows the initial page displayed after recognition is complete, which includes the recognition result (pizza in palo alto) as well as the "n-best alternatives" (additional hypotheses from the recognizer) which are viewable by tapping on the phrase to display a drop-down list (note the down arrow on the right-hand side of the text field). The user can initiate a new search by voice or by typing. As shown, the first three results are displayed in the browser, but tapping on "Map all results" delivers the full set of results in Google Maps, as shown on the right. The maps interface shows the relative location of each listing as well as the user's contacts (note the blue box in the upper right-hand corner). Tapping the business name above the map pin provides more details.


4:56 PM

pizza in palo alto

Web — Options

Local results for **pizza in palo alto** — Palo Alto, CA

Patxi's Chicago **Pizza**
37 reviews
441 Emerson St, Palo Alto, CA 94301
Show map
(650) 473-9999
Get Directions

Pizza My Heart
19 reviews
220 University Avenue, Palo Alto, CA 94301-1711
Show map
(650) 327-9400
Get Directions

Pizza Chicago
26 reviews
4115 El Camino Real, Palo Alto, CA 94306
Show map
(650) 424-9400
Get Directions

More local results — Map all results

Patxi's Chicago **Pizza**
441 Emerson St, **Palo Alto**, 94301 | 650.473.9999
| Sun & Mon 11am - 9pm, Tues - Sat 11am -

Figure 12: Category search using Google search by Voice.

4.1.3 Flexibility and User Control

Another general advantage of mobile voice search is the flexibility and control it affords users.

Unlike with voice-only applications, which prompt users for what to say and how to say it, mobile voice search is completely user-initiated. That is, the user decides what to say, when to say it and how to say it. There's no penalty for starting over or modifying a search. There's no chance of an accidental "hang-up" due to subsequent recognition errors or timeouts. In other words, it's a far cry from the predetermined dialog flows of voice-only applications.

As we discussed earlier, spoken output can be hard to process, but given their flexibility, multi-modal applications can still provide spoken output when it's convenient. Consider queries like "Weather in Palo Alto California", "Flight status of United Airlines 900", "Local time in Bangalore", "Fifty pounds in US dollars". These types of queries have short answers, exactly the kind suited for spoken output, especially in eyes-busy contexts.

Still, the flexibility associated with multi-modal applications turns out to be a double-edged sword. More user control and choices also leads to more potential distractions. The application must still make it clear what the user can say in terms of available features. For example, in addition to web search, Google's Android platform also includes speech shortcuts for its maps navigation feature, e.g., "Navigate to the Golden Gate Bridge", as well as voice dialing shortcuts such as "Call Tim Jones." More fundamental is making sure users know how to use the speech recognition feature in the first place given all the features available. Designers are faced with a series of hard questions: How should voice search be triggered? Should it be a button? A gesture? Both? What kind of button? Should it be held and released? Tapped once? Tapped twice? What kind of feedback should be displayed? Should it include audio? We address these and other questions in the subsections that follow.

4.2 Challenges in Multi-Modal Interface Design

4.2.1 Capturing the Utterance: Buttons, Actions and Feedback

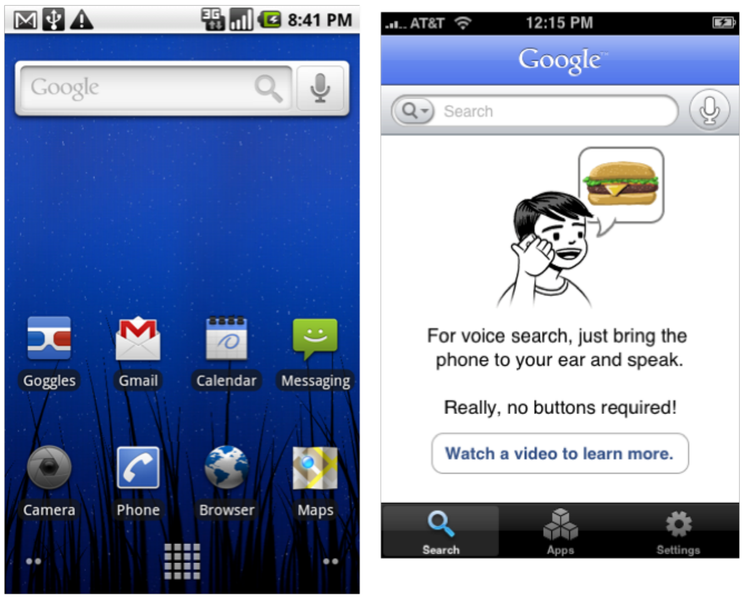
Capturing clear and complete user utterances is of paramount importance to any speech application. However, even if everything is done to ensure that the signal is clean and the microphone is working properly, there are factors in the user interface itself which will affect the interaction.

On the face of it, pressing a button to initiate speech seems pretty simple. But once you consider the types of buttons available on mobile devices as well as the actions possible for each type of button, and further the size of the button and where it's placed on the screen, things become more complex. Google uses different strategies depending on the device.

Devices running Android have the microphone button on the right-hand side of the search box typically located at the top of the home touch screen. This is similar to the button on Google Mobile App (GMA) for the iPhone, which also uses a touch screen. Both are shown in Figure 13.

As shown above, both microphone buttons are relatively small, which raises the obvious question as to whether a bigger button would make it easier for users to trigger voice search or perhaps users would more easily discover the feature in the first place. Alternatively, the button could remain the same size but with a larger target area to trigger the action. This is currently the case in the GMA interface, shown on the right. So far, there is no evidence that the larger target area is making it any easier to trigger as compared to the Android button.

Then there's the placement of the button. In the examples shown above, the upper right-hand corner location may not be a factor when the user holds the phone with one hand and presses the button with the other. However,



For voice search, just bring the phone to your ear and speak.

Really, no buttons required!

Figure 13: Android Nexus One and Google Mobile App (GMA) on iPhone.

some users prefer to initiate speech with one hand. In this case, it may make a difference whether the user is right or left handed. Other such ergonomics-based suggestions have been proposed such as locating a larger button across the bottom of the screen so that users can hold the phone in one hand and more easily press the button with their thumb.

It should also be pointed out that there is a physical ”search” key on all Android phones. A regular press (one tap) simply brings up the search widget from any context (i.e., no matter which app the users has open). However, long-pressing this button (holding it down for a second or so) brings up voice search. The long press is a common feature for Android as it is used in many contexts, that is, not just on physical buttons but on the touch screen itself. Note that this is not the same as the hold-and-speak, walkie-talkie action which is used for the BlackBerry and S60 versions of GMA, which we discuss later.

4.2.2 Button Actions

While most mobile speech apps require the user to press a button to initiate recording, only some require the user to manually stop the recording after speaking by pressing it again, or pressing another button. In the examples discussed in Figure 2 above, both applications make use of an ”endpointer”, which is software that automatically determines when the speaker’s utterance is complete (i.e., it finds the ”end point”). This is the same strategy used in most speech-based telephone applications. While endpointers may be convenient for mobile speech, they seem to be better suited for applications like web search or voice commands in which the input is shorter, generally one phrase. This is because silence is a primary factor used to determine the end point of the utterance. In this way, applications that must tolerate longer periods of silence between phrases as in dictation or singing often require the user to tap the button once to begin and then a second time to manually end recording.

Another way to manually endpoint is to press and hold the button while speaking. This is based on the ”walkie talkie” model. GMA employs this strategy on platforms with physical buttons, namely the BlackBerry as well as S60 platform phones. While the press-and-hold strategy seems intuitive and certainly has its fans, a common problem is the tendency to release the button before finishing the utterance. This premature endpointing in turn causes the utterance to be truncated, usually resulting in misrecognition.

4.2.3 Gesture-Based Speech Triggers

Putting buttons aside for the moment, gesture-based triggers for initiating speech are another strategy which has been implemented in the iPhone version of GMA, as shown on the right-hand screen in Figure 13 above.

As the home screen hint says, voice search will trigger without a button press when the user simply raises the phone to his or her ear as this type of movement is detected by tapping into the phone’s accelerometer. While it turns out that many users like this feature (fully one third of voice searches on GMA for iPhone are triggered by this gesture), others still don’t realize it exists despite the rather explicit hint shown on the splash screen. A Google internal study also showed that some users, while aware of the feature, prefer to keep their eyes on the screen at all times, something that’s not possible when using this gesture.

4.2.4 Feedback

Even when users understand how to initiate speech, subsequent user interface feedback plays an important role. For example, in an early pre-launch design of voice search for GMA for iPhone, the word ”listening” was used on the screen that appeared after the user pressed the microphone button.

The designers assumed users would understand that ”listening” clearly indicated that it was time for the user to speak. However, in several cases, the participants intently watched the ”listening” screen but said nothing. When asked what the application might be doing, the users responded that device was ”listening” to somehow calibrate the ambient noise–making sure noise levels were right. As a result, the application took a more direct approach. As shown in Fig 14, all of Google’s mobile voice features begin with ”Speak now”. In addition, they give clear feedback on the level of the speaker’s voice indicated in the Android case below by the microphone filling up as the level increases.

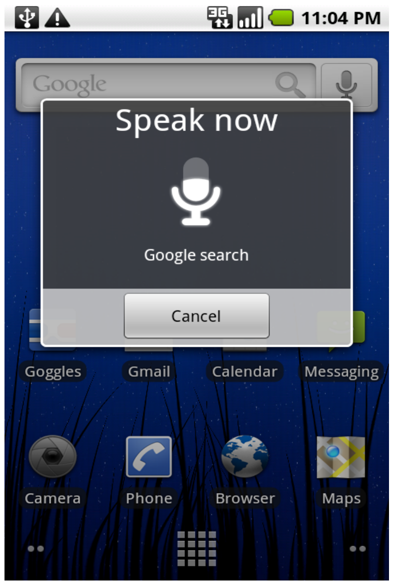


Figure 14: Feedback during speech input.

Making sure the recognizer at least starts with a clean and complete recording of what the user actually said is key for any speech application. As we’ve seen, this is far from automatic and many strategies are currently in use. It may be that some are equally effective and address different user preferences. However, we are also likely to discover that some are simply more effective.

4.3 Correction: Displaying Alternative Recognition Hypotheses

4.3.1 The N-Best List

Speech recognition isn't perfect and designing speech-based applications requires paying special attention to these inevitable errors. One important design puzzle involves making what is referred to as the "n-best list" more accessible and visible to users. This is a list of alternative recognition hypotheses returned by the recognizer. For example, suppose the user says "Holy day in South America". The recognizer may return "holiday inn south america" as the top hypothesis but include what the user actually said in the list. It may also be the case that what the user said isn't in the list but there are alternatives that are sufficiently related. In these scenarios, making sure the n-best is easily accessible saves the user the frustration of having to re-speak the utterance and fosters a more positive impression of the application in general.

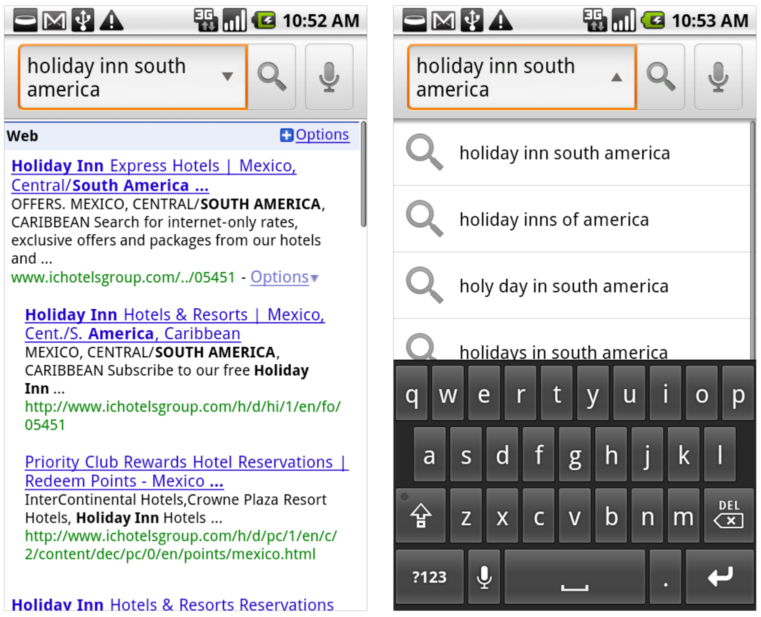
4.3.2 Design Strategies

Figure 15 below shows how Android displays the n-best list. A similar strategy is used in GMA for iPhone as well as for the BlackBerry and S60 platform.

As shown on the left, only the top hypothesis is displayed on the results screen. The down-arrow indicator is used to bring attention to the n-best list which is displayed if the user taps anywhere inside the text field. The right-hand screen shows the list displayed. As it turns out, this design isn't effective as we'd like as only a small percentage of users are tapping on the phrase to reveal the list even when it would be helpful (i.e., when it contains the correct alternative or a related phrase).

4.3.3 Possible Solutions

There are several reasons for this. It may be that the drop down list isn't obvious and we need a more prominent hint. Or it may be that users are aware of the drop down but are not sure what the list is for. That is, it could be that users don't realize that tapping on the alternative would initiate a new search. It could also be that users don't find it's worth the trouble to tap the list just to see if the alternative is there and decide they might as well just re-speak the phrase.


10:52 AM

holiday inn south america

Web Options

Holiday Inn Express Hotels | Mexico, Central/**South America ...**
OFFERS. MEXICO, CENTRAL/**SOUTH AMERICA**, CARIBBEAN Search for internet-only rates, exclusive offers and packages from our hotels and ...
www.ichotelsgroup.com/../05451 - Options

Holiday Inn Hotels & Resorts | Mexico, Cent./S. **America**, Caribbean
MEXICO, CENTRAL/**SOUTH AMERICA**, CARIBBEAN Subscribe to our free **Holiday Inn** ...
http://www.ichotelsgroup.com/h/d/hi/1/en/fo/05451

Priority Club Rewards Hotel Reservations | Redeem Points - Mexico ...
InterContinental Hotels,Crowne Plaza Resort Hotels, **Holiday Inn** Hotels ...
http://www.ichotelsgroup.com/h/d/pc/1/en/c/2/content/dec/pc/0/en/points/mexico.html

Holiday Inn Hotels & Resorts Reservations

10:53 AM

holiday inn south america

holiday inn south america

holiday inns of america

holy day in south america

holidays in south america

Figure 15: Displaying n-best on Android.

Possible solutions will only emerge as we experiment with alternative designs. One idea is to make the n-best list more prominent by displaying a pop-up hint or even flashing the list for a second or two as the results load. However, we must also make sure not to burden users when the list is irrelevant either because the correct alternative isn't there or the top hypothesis is already correct. In general speed is king for mobile user interfaces and we try to do as little as possible to get in the way of displaying the results. This problem of relevance might be solved by taking advantage of the confidence score returned with the results. That is, the recognizer returns a score roughly indicating "how sure" it is the phrases it returns are what the user said. In this way, the design could more aggressively draw attention to the list when the confidence is lower and leave it as is otherwise. This experiment is in fact underway now but we'll have to wait and see if it addresses all the user interface factors at play.

The problem of correction becomes even more complex when designing for dictation interfaces, where the correction of one phrase might affect the compatibility of preceding or subsequent phrases, for example. But dictation goes beyond the scope of this discussion.

4.4 Beyond Search

4.4.1 Non-Search Voice Commands

Subsequent releases of the Android platform included new voice shortcuts using the same interface they'd used for search (i.e., the same mic button and initial dialog screens). For example "Navigate to the Golden Gate Bridge" jumps straight to the Google Maps navigation feature and begins giving directions as though the user had tapped through and entered the destination by hand. Other commands like "Call John Smith at home" or "Map of Chelsea, Manhattan" likewise provide quick and easy ways to access embedded application functions just by speaking a phrase.

4.4.2 Challenges and Possible Solutions

This new functionality comes with a price, however. To quickly launch the features, particular phrases like "navigate to", "map of", "directions to", "call", etc. were mapped to each shortcut. However, it's well known that users tend to paraphrase when faced with formulating the command on the fly especially of the targeted phrase is something unfamiliar or that doesn't match their own language patterns. For example, just because I once learned that the phrase "navigate to" will trigger the Google Maps feature in one step doesn't mean I will remember that exact phrase when I need it. In fact, I am likely to substitute the phrase with a synonymous phrase like "Take me to" or "Drive to".

There are short-term and longer terms solutions for this. First, similar to the n-best list situation, contextually significant and visually prominent hints can help a great deal to remind users what the working phrases are. Subsequent designs for these features on Android will in fact include them. However, does this go far enough?

4.4.3 Predicting User Intent

Rather than requiring users to memorize specific phrases, a better solution would be for users to choose there own shortcut phrases. That is, they could say what they wanted and it would "just work". Of course, this is easier said than done. The linguistic possibilities are endless and semantic parsing capabilities would be required to even begin to return reasonable candidates for what the user might have said. What's more, unlike search, in this case you would be combining possible results for very different actions. "Call of the Wild" is a search while or "Call Owen Wilde" is a contact dialing action, yet the two sound very similar. At the very least the application would need to display disambiguation lists much more often than it currently does so that the user could choose the option that he or she intended (if it's there) and reinforce the feedback loop for better results. However this would add an extra step before results could be displayed or the action could be carried out.

Automatically knowing what users mean based on speech input is clearly a longer term project. However, from a user's perspective it isn't likely to be thought of as very different from what is currently offered in mobile apps. Think of Google Search by Voice: Users already say whatever phrase they want and are given a list of choices, often with the one they wanted listed right at the top.

5 User Studies

What are people looking for when they are mobile? What factors influence them to choose to search by voice or type? What factors contribute to user happiness? How do we maintain and grow our user base? How can speech make information access easier? In this section we explore these questions based on analysis of live data. We discuss the behavior of our users and how these impact our decisions about technology and user interfaces.

5.1 What do Users Choose to Speak?

In this section, we discuss the search patterns of voice search users. We investigate the use cases for search by voice, and how they differ from other methods of communicating a query to a search engine. We address these questions empirically, by looking at the server logs across various search platforms and input modalities.

Our data set consists of the search logs for all users of GMA on all mobile platforms in the United States who issued queries during a 4-week (28-day) period during the summer of 2009. For a baseline, we also analyze search queries to the "desktop" (i.e., non-mobile) version of google.com.

In general we find the distribution of voice search queries to be surprisingly similar to the distributions for both mobile web search and desktop queries, but there are a number of interesting differences.

5.1.1 By Topic

We aggregated a recent month of our search server logs by the broad topic of the query using an automatic classification scheme described in Kamvar and Baluja [6]. The chart below illustrates the relative difference between spoken and typed queries for eight popular categories. Each bar is normalized so that 1.0 represents the frequency of that category for desktop websearch.

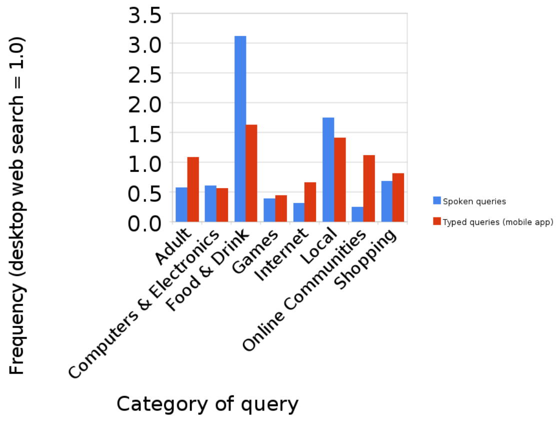


Figure 16: Category of query.

Queries in the "Local" category are those whose results have a regional emphasis. They include queries for business listings (e.g., “Starbucks”) but can also include places (e.g., “Lake George”) or properties relating to a place (“weather Holmdel NJ”, “best gas prices”). Food & Drink queries are self-descriptive and are often queries for major food chains (e.g., “Starbucks”), or genres of food & drink (e.g., “tuna fish”, “Mexican food”). Both of these query types likely relate to a user’s location, even if there is no location specified in the query (this facilitated by the My Location feature which will automatically generate local results for a query). Shopping and Travel queries are likely to relate either to a user’s situational context (their primary activity at the time of querying), or to their location. Example Shopping queries include “Rapids water park coupons” which may indicate the user is about to enter a water park, and “black Converse shoes” which may indicate she would like to compare shoe prices. Queries such as “Costco” and “Walmart” also fall in the Shopping category, but likely relate to a user’s location, as the My Location feature automatically generates local results for these queries. Likewise, Travel queries such as “Metro North train schedule” and “flight tracker” may relate to a user’s situational context, and queries such as “Las Vegas tourism” may relate to their location.

In summary, an examination of the category distribution by input method of the query shows the following salient differences:

- **Voice searches are more likely to be about an ”on-the-go” topic:** Mobile queries, and voice searches in particular, have a much greater emphasis on categories such as food and drink and local businesses.
- **Voice searches are less likely to be about a potentially sensitive subject:** Categories that consist of sensitive content (adult themes, social networking, and health) are avoided by voice search users, relatively speaking. This may be because they wish to preserve their privacy in a public setting.
- **Voice searches are less likely to be for a website that requires significant interaction:** Voice searches are relatively rarely about the sorts of topics that require significant interaction following the search, such as games and social networking.

5.1.2 By Other Attributes

We built straightforward classifiers to detect whether a query contains a geographical location, whether a query is a natural language question (such as ”Who is the President of the United States?”), and whether the query is simply for a URL such as ”amazon.com”. The results for the same sample of query data used above is illustrated in the following chart:

Queries that include a location term such as ”Mountain View” are more popular in voice search than in typed mobile search, reinforcing the result above about the broad category of local services being more popular.

Question queries, defined simply as queries that begin with a ”wh” question word or ”how”, are far more popular in the voice context. This may reflect the tendency of the speech user to feel more like they’re in a dialog than issuing a search engine query. Another explanation is questions of this sort arise more frequently in an on-the-go context (such as ”settling a bet” with friends about a factual matter).

Queries for URLs such as ”amazon.com” or ”times.com” are rare relative to desktop search, and rarer still relative to typed mobile queries. This reflects the fact that users tend to want information directly from their voice search experience; they are far less likely to be in a position to interact with a web site.

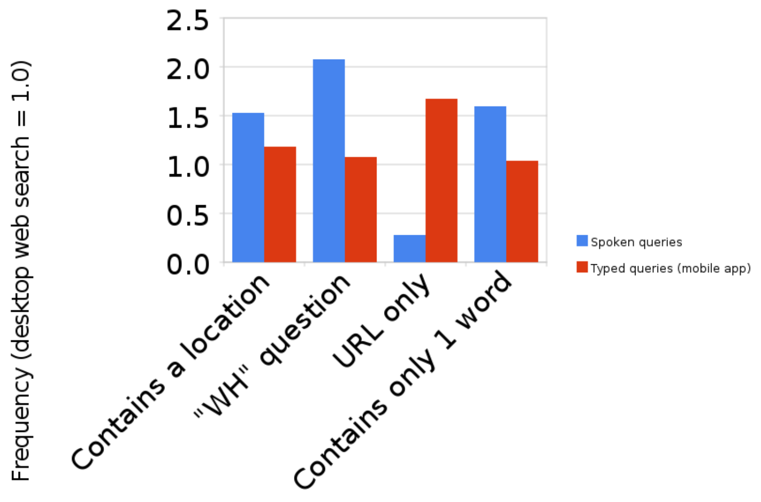


Figure 17: Attribute of query.

Reinforcing this, we have found that users are less likely to click on links returned from voice search queries than they are to click on links returned from desktop search queries, even accounting for recognition errors. This appears to be primarily because users more often pose queries that can be answered on the results page itself. Also, given current mobile network speeds, users may be reluctant to wait for an additional web page to load. Finally, voice search users are more likely to be in a context in which it's difficult to click at all.

Finally, we find that short queries, in particular 1 and 2 word queries, are relatively more frequent in voice searches than in typed searches, and longer queries (¿ 5 words) are far rarer. As a result, the average query length is significantly shorter for spoken queries: 2.5 words, as compared with 2.9 words for typed mobile search and 3.1 words for typed desktop search. This result may seem counterintuitive, given that longer queries should be relatively easier to convey by voice. There are numerous possible explanations for this that we have not fully explored. For example, users may avoid longer queries because they are harder to "buffer" prior to speaking; or, the popular queries within the topics favored by voice search users may themselves be shorter.

Keyboard type	Percentage of users	Percentage of queries that are spoken
Full	86.9%	34.6%
Compressed	13.1%	41.6%

Table 6: A comparison of voice search usage for BlackBerry keyboard types. The data is based on a sample of 1.3 million queries from a 4-week period in the summer of 2009

5.1.3 Keyboard considerations

In characterizing what distinguishes voice queries from typed queries, it matters, of course, what kind of keyboard is available to the user. For some insight on this we can look at the subset of our data from users of the BlackBerry version of GMA, which serves a number of different phone models. BlackBerry phones have two common keyboard types: a full qwerty keyboard which assigns one letter per key, and a compressed keyboard which assigns two letters for most of the keys.

Compressed keyboards make query entry more inefficient because more keypresses are needed on average to enter a query. This becomes clear when we look at the fraction of queries that are spoken rather than typed on these models, which favors the compressed keyboard by 20% relative (Table 6):

5.2 When do Users Continue to Speak?

The above section gave a glimpse of the characteristics of voice queries. This section looks at what factors influence whether a user chooses to search by voice rather than typing their query when they have both options available to them. Do certain factors cause them to give up using voice search entirely? Whether or not a user continues to view voice as a viable option was a matter of great importance in prioritizing efforts in the early stages of developing this product.

We have systematically measured the factors that influence whether a user continues to search by voice, and found that recognition accuracy is the most important factor. There is a strong positive relationship between recognition accuracy and the probability that a user returns, more so than other factors we considered – latency, for example – though these factors matter too.

Our analysis technique is to look at the behavior of a group of (anonymous) users in two different time intervals, spaced a short time apart, to see if certain factors were correlated with the users staying or dropping out between the two intervals. Figure 18 summarizes the finding for recognizer confidence, which we use as a proxy for accuracy. Here, ”period A” is the first week of November, 2009, and ”period B” is the third week of November, 2009. Each of the 10 buckets along the x axis signifies the subset of users in period A whose final voice query had a particular confidence estimate according to the recognizer. The blue bar signifies the fraction of users in each bucket; for example, about 30% of users had a final query with confidence greater than 0.9. The red bar signifies the fraction of these users who returned to make voice searches in period B, normalized by our overall average retention rate. In summary, the users with final confidence greater than 0.6 were more likely than average to continue using voice search, and the other users, less likely.

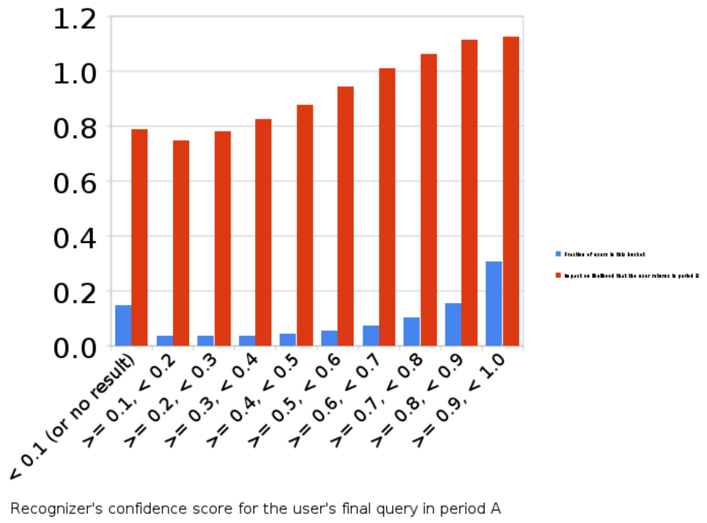


Figure 18: User growth as a function of recognizer confidence.

6 Conclusions

The emergence of more advanced mobile devices, fast access to incredibly accurate (or high quality) search engines and a powerful server side infrastructure (cloud computing) made mobile computing possible. Speech is a natural addition and provides a whole new way to search the web.

To this end we have invested heavily in advancing the state of the art.

The combination of a vast amount of data resources, computational resources, and innovation has created an opportunity to make speech as common place and useful as any other input modality on the phone.

Acknowledgments

Google search by Voice is a culmination of years of effort in the speech and mobile group at Google. The authors would like to thank all those involved in working on this project and making Google search by voice a reality.

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