

# You Had Me at Hello: How Phrasing Affects Memorability

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## Abstract

Understanding the ways in which information achieves widespread public awareness is a research question of significant interest. We consider whether, and how, the way in which the information is phrased — the choice of words and sentence structure — can affect this process. To this end, we develop an analysis framework and build a corpus of movie quotes, annotated with memorability information, in which we are able to control for both the speaker and the setting of the quotes. We find that there are significant differences between memorable and non-memorable quotes in several key dimensions, even after controlling for situational and contextual factors. One is *lexical distinctiveness*: in aggregate, memorable quotes use less common word choices, but at the same time are built upon a scaffolding of common syntactic patterns. Another is that memorable quotes tend to be more *general* in ways that make them easy to apply in new contexts — that is, more portable. We also show how the concept of “memorable language” can be extended across domains.

## 1 Hello. My name is Inigo Montoya.

Understanding what items will be retained in the public consciousness, and why, is a question of fundamental interest in many domains, including marketing, politics, entertainment, and social media; as we all know, many items barely register, whereas others catch on and take hold in many people’s minds.

An active line of recent computational work has employed a variety of perspectives on this question.

Building on a foundation in the sociology of diffusion [27, 31], researchers have explored the ways in which network structure affects the way information spreads, with domains of interest including blogs [1, 11], email [37], on-line commerce [22], and social media [2, 28, 33, 38]. There has also been recent research addressing temporal aspects of how different media sources convey information [23, 30, 39] and ways in which people react differently to information on different topics [28, 36].

Beyond all these factors, however, one’s everyday experience with these domains suggests that the way in which a piece of information is expressed — the choice of words, the way it is phrased — might also have a fundamental effect on the extent to which it takes hold in people’s minds. Concepts that attain wide reach are often carried in messages such as political slogans, marketing phrases, or aphorisms whose language seems intuitively to be memorable, “catchy,” or otherwise compelling.

Our first challenge in exploring this hypothesis is to develop a notion of “successful” language that is precise enough to allow for quantitative evaluation. We also face the challenge of devising an evaluation setting that separates the phrasing of a message from the conditions in which it was delivered — highly-cited quotes tend to have been delivered under compelling circumstances or fit an existing cultural, political, or social narrative, and potentially what appeals to us about the quote is really just its invocation of these extra-linguistic contexts. Is the form of the language adding an effect *beyond or independent of* these (obviously very crucial) factors? To investigate the question, one needs a way of control-

ling — as much as possible — for the role that the surrounding context of the language plays.

**The present work (i): Evaluating language-based memorability** Defining what makes an utterance memorable is subtle, and scholars in several domains have written about this question. There is a rough consensus that an appropriate definition involves elements of both *recognition* — people should be able to retain the quote and recognize it when they hear it invoked — and *production* — people should be motivated to refer to it in relevant situations [15]. One suggested reason for why some memes succeed is their ability to provoke emotions [16]. Alternatively, memorable quotes can be good for expressing the feelings, mood, or situation of an individual, a group, or a culture (the *zeitgeist*): “Certain quotes exquisitely capture the mood or feeling we wish to communicate to someone. We hear them ... and store them away for future use” [10].

None of these observations, however, serve as definitions, and indeed, we believe it desirable to not pre-commit to an abstract definition, but rather to adopt an operational formulation based on external human judgments. In designing our study, we focus on a domain in which (i) there is rich use of language, some of which has achieved deep cultural penetration; (ii) there already exist a large number of external human judgments — perhaps implicit, but in a form we can extract; and (iii) we can control for the setting in which the text was used.

Specifically, we use the complete scripts of roughly 1000 movies, representing diverse genres, eras, and levels of popularity, and consider which lines are the most “memorable”. To acquire memorability labels, for each sentence in each script, we determine whether it has been listed as a “memorable quote” by users of the widely-known IMDb (the Internet Movie Database), and also estimate the number of times it appears on the Web. Both of these serve as memorability metrics for our purposes.

When we evaluate properties of memorable quotes, we compare them with quotes that are not assessed as memorable, but were spoken by the same character, at approximately the same point in the same movie. This enables us to control in a fairly fine-grained way for the confounding effects of context discussed above: we can observe differences

that persist even after taking into account both the speaker and the setting.

In a pilot validation study, we find that human subjects are effective at recognizing the more IMDb-memorable of two quotes, even for movies they have not seen. This motivates a search for features intrinsic to the text of quotes that signal memorability. In fact, comments provided by the human subjects as part of the task suggested two basic forms that such textual signals could take: subjects felt that (i) memorable quotes often involve a *distinctive* turn of phrase; and (ii) memorable quotes tend to invoke *general* themes that aren’t tied to the specific setting they came from, and hence can be more easily invoked for future (out of context) uses. We test both of these principles in our analysis of the data.

**The present work (ii): What distinguishes memorable quotes** Under the controlled-comparison setting sketched above, we find that memorable quotes exhibit significant differences from non-memorable quotes in several fundamental respects, and these differences in the data reinforce the two main principles from the human pilot study. First, we show a concrete sense in which memorable quotes are indeed *distinctive*: with respect to lexical language models trained on the newswire portions of the Brown corpus [21], memorable quotes have significantly lower likelihood than their non-memorable counterparts. Interestingly, this distinctiveness takes place at the level of words, but not at the level of other syntactic features: the part-of-speech composition of memorable quotes is in fact more likely with respect to newswire. Thus, we can think of memorable quotes as consisting, in an aggregate sense, of unusual word choices built on a scaffolding of common part-of-speech patterns.

We also identify a number of ways in which memorable quotes convey greater *generality*. In their patterns of verb tenses, personal pronouns, and determiners, memorable quotes are structured so as to be more “free-standing,” containing fewer markers that indicate references to nearby text.

Memorable quotes differ in other interesting aspects as well, such as sound distributions.

Our analysis of memorable movie quotes suggests a framework by which the memorability of text in a range of different domains could be investigated.

We provide evidence that such cross-domain properties may hold, guided by one of our motivating applications in marketing. In particular, we analyze a corpus of advertising slogans, and we show that these slogans have significantly greater likelihood at both the word level and the part-of-speech level with respect to a language model trained on memorable movie quotes, compared to a corresponding language model trained on non-memorable movie quotes. This suggests that some of the principles underlying memorable text have the potential to apply across different areas.

**Roadmap** §2 lays the empirical foundations of our work: the design and creation of our movie-quotes dataset, which we make publicly available (§2.1), a pilot study with human subjects validating IMDb-based memorability labels (§2.2), and further study of incorporating search-engine counts (§2.3). §3 details our analysis and prediction experiments, using both movie-quotes data and, as an exploration of cross-domain applicability, slogans data. §4 surveys related work across a variety of fields. §5 briefly summarizes and indicates some future directions.

## 2 I’m ready for my close-up.

### 2.1 Data

To study the properties of memorable movie quotes, we need a source of movie lines and a designation of memorability. Following [8], we constructed a corpus consisting of all lines from roughly 1000 movies, varying in genre, era, and popularity; for each movie, we then extracted the list of quotes from IMDb’s *Memorable Quotes* page corresponding to the movie.<sup>1</sup>

A memorable quote in IMDb can appear either as an individual sentence spoken by one character, or as a multi-sentence line, or as a block of dialogue involving multiple characters. In the latter two cases, it can be hard to determine which particular portion is viewed as memorable (some involve a build-up to a punch line; others involve the follow-through after a well-phrased opening sentence), and so we focus in our comparisons on those memorable quotes that

<sup>1</sup>This extraction involved some edit-distance-based alignment, since the exact form of the line in the script can exhibit minor differences from the version typed into IMDb.

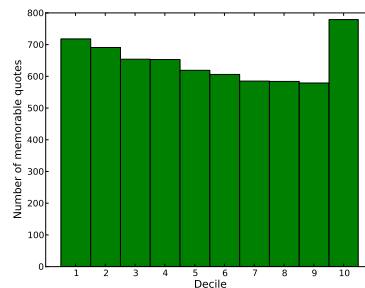


Figure 1: Location of memorable quotes in each decile of movie scripts (the first 10th, the second 10th, etc.), summed over all movies. The same qualitative results hold if we discard each movie’s very first and last line, which might have privileged status.

appear as a single sentence rather than a multi-line block.<sup>2</sup>

We now formulate a task that we can use to evaluate the features of memorable quotes. Recall that our goal is to identify effects based in the language of the quotes themselves, beyond any factors arising from the speaker or context. Thus, for each (single-sentence) memorable quote  $M$ , we identify a non-memorable quote that is as similar as possible to  $M$  in all characteristics but the choice of words. This means we want it to be spoken by the same character in the same movie. It also means that we want it to have the same length: controlling for length is important because we expect that on average, shorter quotes will be easier to remember than long quotes, and that wouldn’t be an interesting textual effect to report. Moreover, we also want to control for the fact that a quote’s position in a movie can affect memorability: certain scenes produce more memorable dialogue, and as Figure 1 demonstrates, in aggregate memorable quotes also occur disproportionately near the beginnings and especially the ends of movies. In summary, then, for each  $M$ , we pick a contrasting (single-sentence) quote  $N$  from the same movie that is as close in the script as possible to  $M$  (either before or after it), subject to the conditions that (i)  $M$  and  $N$  are uttered by the same speaker, (ii)  $M$  and  $N$  have the same number of words, and (iii)  $N$  does not occur in the IMDb list of memorable

<sup>2</sup>We also ran experiments relaxing the single-sentence assumption, which allows for stricter scene control and a larger dataset but complicates comparisons involving syntax. The non-syntax results were in line with those reported here.

Movie	First Quote	Second Quote
Jackie Brown	Half a million dollars will always be missed.	I know the type, trust me on this.
Star Trek: Nemesis	I think it's time to try some unsafe velocities.	No cold feet, or any other parts of our anatomy.
Ordinary People	A little advice about feelings kiddo; don't expect it always to tickle.	I mean there's someone besides your mother you've got to forgive.

Table 1: Three example pairs of movie quotes. Each pair satisfies our criteria: the two component quotes are spoken close together in the movie by the same character, have the same length, and one is labeled memorable by the IMDb while the other is not. (Contractions such as “it’s” count as two words.)

quotes for the movie (either as a single line or as part of a larger block).

Given such pairs, we formulate a *pairwise comparison task*: given  $M$  and  $N$ , determine which is the memorable quote. Psychological research on subjective evaluation [35], as well as initial experiments using ourselves as subjects, indicated that this pairwise set-up easier to work with than simply presenting a single sentence and asking whether it is memorable or not; the latter requires agreement on an “absolute” criterion for memorability that is very hard to impose consistently, whereas the former simply requires a judgment that one quote is more memorable than another.

Our main dataset, available at <http://www.cs.cornell.edu/~cristian/memorability.html>,<sup>3</sup> thus consists of approximately 2200 such  $(M, N)$  pairs, separated by a median of 5 same-character lines in the script. The reader can get a sense for the nature of the data from the three examples in Table 1.

We now discuss two further aspects to the formulation of the experiment: a preliminary pilot study involving human subjects, and the incorporation of search engine counts into the data.

## 2.2 Pilot study: Human performance

As a preliminary consideration, we did a small pilot study to see if humans can distinguish memorable from non-memorable quotes, assuming our IMDb-induced labels as gold standard. Six subjects, all native speakers of English and none an author of this paper, were presented with 11 or 12 pairs of memorable vs. non-memorable quotes; again, we controlled for extra-textual effects by ensuring that in each pair the two quotes come from the same movie, are by the same character, have the same length, and

<sup>3</sup>Also available there: other examples and factoids.

subject	number of matches with IMDb-induced annotation
A	11/11 = 100%
B	11/12 = 92%
C	9/11 = 82%
D	8/11 = 73%
E	7/11 = 64%
F	7/12 = 58%
macro avg	— 78%

Table 2: Human pilot study: number of matches to IMDb-induced annotation, ordered by decreasing match percentage. For the null hypothesis of random guessing, these results are statistically significant,  $p < 2^{-6} \approx .016$ .

appear as nearly as possible in the same scene.<sup>4</sup> The order of quotes within pairs was randomized. Importantly, because we wanted to understand whether the language of the quotes by itself contains signals about memorability, we chose quotes from movies that the subjects said they had not seen. (This means that each subject saw a different set of quotes.) Moreover, the subjects were requested not to consult any external sources of information.<sup>5</sup> The reader is welcome to try a demo version of the task at <http://www.cs.cornell.edu/~cristian/memorability.html>.

Table 2 shows that all the subjects performed (sometimes much) better than chance, and against the null hypothesis that all subjects are guessing randomly, the results are statistically significant,  $p < 2^{-6} \approx .016$ . These preliminary findings provide evidence for the validity of our task: despite the apparent difficulty of the job, even humans who haven’t seen the movie in question can recover our IMDb-

<sup>4</sup>In this pilot study, we allowed multi-sentence quotes.

<sup>5</sup>We did not use crowd-sourcing because we saw no way to ensure that this condition would be obeyed by arbitrary subjects. We do note, though, that after our research was completed and as of Apr. 26, 2012,  $\approx 11,300$  people completed the online test: average accuracy: 72%, mode number correct: 9/12.

induced labels with some reliability.<sup>6</sup>

### 2.3 Incorporating search engine counts

Thus far we have discussed a dataset in which memorability is determined through an explicit labeling drawn from the IMDb. Given the “production” aspect of memorability discussed in §1, we should also expect that memorable quotes will tend to appear more extensively on Web pages than non-memorable quotes; note that incorporating this insight makes it possible to use the (implicit) judgments of a much larger number of people than are represented by the IMDb database. It therefore makes sense to try using search-engine result counts as a second indication of memorability.

We experimented with several ways of constructing memorability information from search-engine counts, but this proved challenging. Searching for a quote as a stand-alone phrase runs into the problem that a number of quotes are also sentences that people use without the movie in mind, and so high counts for such quotes do not testify to the phrase’s status as a memorable quote from the movie. On the other hand, searching for the quote in a Boolean conjunction with the movie’s title discards most of these uses, but also eliminates a large fraction of the appearances on the Web that we want to find: precisely because memorable quotes tend to have widespread cultural usage, people generally don’t feel the need to include the movie’s title when invoking them. Finally, since we are dealing with roughly 1000 movies, the result counts vary over an enormous range, from recent blockbusters to movies with relatively small fan bases.

In the end, we found that it was more effective to use the result counts in conjunction with the IMDb labels, so that the counts played the role of an additional filter rather than a free-standing numerical value. Thus, for each pair  $(M, N)$  produced using the IMDb methodology above, we searched for each of  $M$  and  $N$  as quoted expressions in a Boolean conjunction with the title of the movie. We then kept only those pairs for which  $M$  (i) produced more than five results in our (quoted, conjoined) search, and (ii) produced at least twice as many results as the cor-

<sup>6</sup>The average accuracy being below 100% reinforces that context is very important, too.

responding search for  $N$ . We created a version of this filtered dataset using each of Google and Bing, and all the main findings were consistent with the results on the IMDb-only dataset. Thus, in what follows, we will focus on the main IMDb-only dataset, discussing the relationship to the dataset filtered by search engine counts where relevant (in which case we will refer to the +Google dataset).

## 3 Never send a human to do a machine’s job.

We now discuss experiments that investigate the hypotheses discussed in §1. In particular, we devise methods that can assess the distinctiveness and generality hypotheses and test whether there exists a notion of “memorable language” that operates across domains. In addition, we evaluate and compare the predictive power of these hypotheses.

### 3.1 Distinctiveness

One of the hypotheses we examine is whether the use of language in memorable quotes is to some extent unusual. In order to quantify the level of distinctiveness of a quote, we take a language-model approach: we model “common language” using the newswire sections of the Brown corpus [21]<sup>7</sup>, and evaluate how distinctive a quote is by evaluating its likelihood with respect to this model — the lower the likelihood, the more distinctive. In order to assess different levels of lexical and syntactic distinctiveness, we employ a total of six Laplace-smoothed<sup>8</sup> language models: 1-gram, 2-gram, and 3-gram word LMs and 1-gram, 2-gram and 3-gram part-of-speech<sup>9</sup> LMs.

We find strong evidence that from a lexical perspective, memorable quotes are more distinctive than their non-memorable counterparts. As indicated in Table 3, for each of our lexical “common language” models, in about 60% of the quote pairs, the memorable quote is more distinctive.

Interestingly, the reverse is true when it comes to

<sup>7</sup>Results were qualitatively similar if we used the fiction portions. The age of the Brown corpus makes it less likely to contain modern movie quotes.

<sup>8</sup>We employ Laplace (additive) smoothing with a smoothing parameter of 0.2. The language models’ vocabulary was that of the entire training corpus.

<sup>9</sup>Throughout we obtain part-of-speech tags by using the NLTK maximum entropy tagger with default parameters.

“common language” model		IMDb-only	+Google
lexical	1-gram	61.13%***	59.21%***
	2-gram	59.22%***	57.03%***
	3-gram	59.81%***	58.32%***
syntactic	1-gram	43.60%***	44.77%***
	2-gram	48.31%	47.84%
	3-gram	50.91%	50.92%

Table 3: Distinctiveness: percentage of quote pairs in which the the memorable quote is more distinctive than the non-memorable one according to the respective “common language” model. Significance according to a two-tailed sign test is indicated using \*-notation (\*\*\*)=“ $p < .001$ ”).

syntax: memorable quotes appear to follow the syntactic patterns of “common language” as closely as or more closely than non-memorable quotes. Together, these results suggest that memorable quotes consist of unusual word sequences built on common syntactic scaffolding.

### 3.2 Generality

Another of our hypotheses is that memorable quotes are easier to use outside the specific context in which they were uttered — that is, more “portable” — and therefore exhibit fewer terms that refer to those settings. We use the following syntactic properties as proxies for the generality of a quote:

- **Fewer 3<sup>rd</sup>-person pronouns**, since these commonly refer to a person or object that was introduced earlier in the discourse. Utterances that employ fewer such pronouns are easier to adapt to new contexts, and so will be considered more general.
- **More indefinite articles** like *a* and *an*, since they are more likely to refer to general concepts than definite articles. Quotes with more indefinite articles will be considered more general.
- **Fewer past tense verbs and more present tense verbs**, since the former are more likely to refer to specific previous events. Therefore utterances that employ fewer past tense verbs (and more present tense verbs) will be considered more general.

Table 4 gives the results for each of these four metrics — in each case, we show the percentage of

Generality metric	IMDb-only	+Google
fewer 3 <sup>rd</sup> pers. pronouns	64.37%***	62.93%***
more indef. article	57.21%***	58.23%***
less past tense	57.91%***	59.74%***
more present tense	54.60%***	55.86%***

Table 4: Generality: percentage of quote pairs in which the memorable quote is more general than the non-memorable ones according to the respective metric. Pairs where the metric does not distinguish between the quotes are not considered.

quote pairs for which the memorable quote scores better on the generality metric.

Note that because the issue of generality is a complex one for which there is no straightforward single metric, our approach here is based on several proxies for generality, considered independently; yet, as the results show, all of these point in a consistent direction. It is an interesting open question to develop richer ways of assessing whether a quote has greater generality, in the sense that people intuitively attribute to memorable quotes.

### 3.3 “Memorable” language beyond movies

One of the motivating questions in our analysis is whether there are general principles underlying “memorable language.” The results thus far suggest potential families of such principles. A further question in this direction is whether the notion of memorability can be extended across different domains, and for this we collected (and distribute on our website) 431 phrases that were explicitly designed to be memorable: advertising slogans (e.g., “Quality never goes out of style.”). The focus on slogans is also in keeping with one of the initial motivations in studying memorability, namely, marketing applications — in other words, assessing whether a proposed slogan has features that are consistent with memorable text.

The fact that it’s not clear how to construct a collection of “non-memorable” counterparts to slogans appears to pose a technical challenge. However, we can still use a language-modeling approach to assess whether the textual properties of the slogans are closer to the memorable movie quotes (as one would conjecture) or to the non-memorable movie quotes. Specifically, we train one language model on memorable quotes and another on non-memorable quotes

(Non)memorable language models		Slogans	Newswire
lexical	1-gram	56.15%**	33.77%***
	2-gram	51.51%	25.15%***
	3-gram	52.44%	28.89%***
syntactic	1-gram	73.09%***	68.27%***
	2-gram	64.04%***	50.21%
	3-gram	62.88%***	55.09%***

Table 5: Cross-domain concept of “memorable” language: percentage of slogans that have higher likelihood under the memorable language model than under the non-memorable one (for each of the six language models considered). Rightmost column: for reference, the percentage of newswire sentences that have higher likelihood under the memorable language model than under the non-memorable one.

Generality metric	slogans	mem.	n-mem.
% 3 <sup>rd</sup> pers. pronouns	2.14%	2.16%	3.41%
% indefinite articles	2.68%	2.63%	2.06%
% past tense	14.60%	21.13%	26.69%

Table 6: Slogans are most general when compared to memorable and non-memorable quotes. (%s of 3<sup>rd</sup> pers. pronouns and indefinite articles are relative to all tokens, %s of past tense are relative to all past and present verbs.)

and compare how likely each slogan is to be produced according to these two models. As shown in the middle column of Table 5, we find that slogans are better predicted both lexically and syntactically by the former model. This result thus offers evidence for a concept of “memorable language” that can be applied beyond a single domain.

We also note that the higher likelihood of slogans under a “memorable language” model is not simply occurring for the trivial reason that this model predicts all other large bodies of text better. In particular, the newswire section of the Brown corpus is predicted better at the lexical level by the language model trained on non-memorable quotes.

Finally, Table 6 shows that slogans employ general language, in the sense that for each of our generality metrics, we see a slogans/memorable-quotes/non-memorable quotes spectrum.

### 3.4 Prediction task

We now show how the principles discussed above can provide features for a basic prediction task, corresponding to the task in our human pilot study:

given a pair of quotes, identify the memorable one.

Our first formulation of the prediction task uses a standard bag-of-words model<sup>10</sup>. If there were no information in the textual content of a quote to determine whether it were memorable, then an SVM employing bag-of-words features should perform no better than chance. Instead, though, it obtains 59.67% (10-fold cross-validation) accuracy, as shown in Table 7. We then develop models using features based on the measures formulated earlier in this section: generality measures (the four listed in Table 4); distinctiveness measures (likelihood according to 1, 2, and 3-gram “common language” models at the lexical and part-of-speech level for each quote in the pair, their differences, and pairwise comparisons between them); and similarity-to-slogans measures (likelihood according to 1, 2, and 3-gram slogan-language models at the lexical and part-of-speech level for each quote in the pair, their differences, and pairwise comparisons between them).

Even a relatively small number of distinctiveness features, on their own, improve significantly over the much larger bag-of-words model. When we include additional features based on generality and language-model features measuring similarity to slogans, the performance improves further (last line of Table 7).

Thus, the main conclusion from these prediction tasks is that abstracting notions such as distinctiveness and generality can produce relatively streamlined models that outperform much heavier-weight bag-of-words models, and can suggest steps toward approaching the performance of human judges who — very much unlike our system — have the full cultural context in which movies occur at their disposal.

### 3.5 Other characteristics

We also made some auxiliary observations that may be of interest. Specifically, we find differences in letter and sound distribution (e.g., memorable quotes — after curse-word removal — use significantly more “front sounds” (labials or front vowels such as represented by the letter *i*) and significantly fewer “back sounds” such as the one represented by *u*),<sup>11</sup>

<sup>10</sup>We discarded terms appearing fewer than 10 times.

<sup>11</sup>These findings may relate to marketing research on *sound symbolism* [7, 19, 40].

Feature set	# feats	Accuracy
bag of words	962	59.67%
distinctiveness	24	62.05%*
generality	4	56.70%
slogan sim.	24	58.30%
<i>all three types together</i>	52	64.27%**

Table 7: Prediction: SVM 10-fold cross validation results using the respective feature sets. Random baseline accuracy is 50%. Accuracies statistically significantly greater than bag-of-words according to a two-tailed t-test are indicated with \*( $p < .05$ ) and \*\*( $p < .01$ ).

word complexity (e.g., memorable quotes use words with significantly more syllables) and phrase complexity (e.g., memorable quotes use fewer coordinating conjunctions). The latter two are in line with our distinctiveness hypothesis.

#### 4 A long time ago, in a galaxy far, far away

How an item’s linguistic form affects the reaction it generates has been studied in several contexts, including evaluations of product reviews [9], political speeches [12], on-line posts [13], scientific papers [14], and retweeting of Twitter posts [36]. We use a different set of features, abstracting the notions of distinctiveness and generality, in order to focus on these higher-level aspects of phrasing rather than on particular lower-level features.

Related to our interest in distinctiveness, work in advertising research has studied the effect of syntactic complexity on recognition and recall of slogans [5, 6, 24]. There may also be connections to Von Restorff’s *isolation effect* Hunt [17], which asserts that when all but one item in a list are similar in some way, memory for the different item is enhanced.

Related to our interest in generality, Knapp et al. [20] surveyed subjects regarding memorable messages or pieces of advice they had received, finding that the ability to be applied to multiple concrete situations was an important factor.

Memorability, although distinct from “memorizability”, relates to short- and long-term recall. Thorn and Page [34] survey sub-lexical, lexical, and semantic attributes affecting short-term memorability of lexical items. Studies of verbatim recall have also considered the task of distinguishing an exact quote from close paraphrases [3]. Investigations of long-term recall have included studies of culturally signif-

icant passages of text [29] and findings regarding the effect of rhetorical devices of alliterative [4], “rhythmic, poetic, and thematic constraints” [18, 26].

Finally, there are complex connections between humor and memory [32], which may lead to interactions with computational humor recognition [25].

#### 5 I think this is the beginning of a beautiful friendship.

Motivated by the broad question of what kinds of information achieve widespread public awareness, we studied the the effect of phrasing on a quote’s memorability. A challenge is that quotes differ not only in how they are worded, but also in who said them and under what circumstances; to deal with this difficulty, we constructed a controlled corpus of movie quotes in which lines deemed memorable are paired with non-memorable lines spoken by the same character at approximately the same point in the same movie. After controlling for context and situation, memorable quotes were still found to exhibit, *on average* (there will always be individual exceptions), significant differences from non-memorable quotes in several important respects, including measures capturing distinctiveness and generality. Our experiments with slogans show how the principles we identify can extend to a different domain.

Future work may lead to applications in marketing, advertising and education [4]. Moreover, the subtle nature of memorability, and its connection to research in psychology, suggests a range of further research directions. We believe that the framework developed here can serve as the basis for further computational studies of the process by which information takes hold in the public consciousness, and the role that language effects play in this process.

**My mother thanks you. My father thanks you. My sister thanks you. And I thank you:** Rebecca Hwa, Evie Kleinberg, Diana Minculescu, Alex Niculescu-Mizil, Jennifer Smith, Benjamin Zimmer, and the anonymous reviewers for helpful discussions and comments; our annotators Steven An, Lars Backstrom, Eric Baumer, Jeff Chadwick, Evie Kleinberg, and Myle Ott; and the makers of Cepacol, Robitussin, and Sudafed, whose products got us through the submission deadline. This paper is based upon work supported in part by NSF grants IIS-0910664, IIS-1016099, Google, and Yahoo!



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