Information Foraging in the Attention Economy Drives the Rising Entropy of English

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Abstract

Over the past 200 years there have been continual advances in communications technology, characterised by increasing ease of access to ever more abundant sources of information. In the face of this abundance, people choose which information to consume and which to ignore. Media producers need attention to survive and so must adapt to this selective pressure, creating a feedback process of co-evolution similar to that seen in many ecosystems. Here, we model people as information foragers who select information diets that maximise their utility rates. This selection drives an increase in the information density (i.e. entropy) of media. The model is extended to describe entropy differences between short-form (e.g. news) and long-form (e.g. books) media. We find empirical evidence of a steady increase in the word entropy of English in diverse media categories since 1900, as well as an accelerated entropy increase in short-form media. Overall, the evidence suggests an increasingly competitive battle for our attention that is having a lasting influence on the evolution of language and communication systems.

In the modern world an abundance of information creates what Herbert Simon has called “a poverty of attention” [1]. As a consequence, information producers must compete for the limited resource of our attention [2, 3, 4]. This dynamic has been called the attention economy, a combination of forces influencing the production and consumption of information, with consequences including a shortening collective attention span [5]. Our proposal here is that competition for attention creates co-evolutionary forces on the evolution and consumption of information much like the co-evolutionary forces proposed by Darwin to describe the relationship between flowering plants and their pollinators [6]. Individuals must choose what to consume in the face of a well-documented rising abundance of information [7]. In turn, information producers must alter their product to match that demand [3]. Here, we show how animal foraging models of diet choice can be adapted to describe how information consumers will alter their choices in response to information proliferation, and then we show how the outcomes of this framework are borne out in language change in English both within and between various types of written media since the year 1900.

Optimal foraging theory describes how animals search for and target different resources in their environment. This evolutionary framework makes and tests predictions about adaptive animal behaviour based on the assumption that animals will optimise fitness through the currency of net energy intake [8]. For example, the prey and patch choice models [9] describe which prey will be included in a forager’s diet and which patches they will choose to forage in. These models have been shown to describe animal behaviour [10, 8], including humans [11, 12, 13, 14, 15], across a wide variety of environments and contexts. A famous result of these diet choice models is that as prey becomes more abundant, a forager will become more selective in their diet [8].

Human foraging for information is an analogous search problem to that of animal foraging [15]. As informavores, human success depends on our ability to efficiently gather and process information. There are remarkable similarities in food foraging behaviour in animals and information foraging behaviour in humans [15]. Pirolli and Card suggested that human information foraging might be an evolutionary exaptation of brain systems that govern food foraging [15]. This connection was later supported by comparative biological studies of neural architecture controlling spatial foraging and the cognitive control of attention [18, 19].

Following initial work by Sandstrom [20], numerous researchers have applied mathematical models from animal foraging to describe the information foraging behaviour of people in different environments,
including web browsing [21] software debugging [22, 23, 24], and the design of information and social environments [21, 24, 25]. We ask here if the same approach might also be used to understand the cultural evolution of media production and consumption in the attention economy.

Information foraging models rest on the foundation of utility maximising agents, a common assumption in economics and artificial intelligence. From an economics perspective, the attention economy has been characterised as a two-sided market where media producers compete for human attention and then sell that attention to advertisers [2]. As such ad-supported media is often given away for free or at nominal cost [2], and competition for attention across all media is mainly based not on price but information utility. Utility here can be defined in terms of revealed preferences [26] — in a competitive environment media producers are driven to produce information that people are attracted to.

Our model outcomes relate to changing utility rates of written media, as such we need a way to quantify the information utility rate of a sample of text. To achieve this, we borrow the idea of information signal entropy from Shannon [27]: the entropy of a source of information is a function of the probability of seeing each symbol given the preceding symbols. For our purposes entropy can be thought of as a rate of information. Estimation of entropy in natural language is non-trivial [28, 29, 30]. Here we use maximum likelihood estimation of the unigram word entropy, which correlates well with more sophisticated entropy estimators [28]. If information foragers gain utility from information then, by definition, an increase in entropy, \( h \), is associated with an increase in utility rate, \( r \),

\[
\frac{\Delta h}{\Delta T_{\text{media}}} \propto r. \tag{1}
\]

We accept that this relation does not capture the actual utility rate of information, or how people are attracted to information. And our model does not fully capture human behaviour and media production. However, the model is instructive as a much simplified approximation of the rich human dynamics, and is borne out by evidence in the aggregate.

The Information and Media Choice Models

An Abundance of Information Drives Increasing Information Utility Rates

When animals hunt for prey they are selective with their diet [8]. In times of scarcity they are less selective [8], for example wolves will take on more difficult prey when starving. And in times of abundance animals are more selective [8] — why waste energy hunting difficult prey when there are plenty of easy calories around? Humans act in the same way when selecting information to consume [15, 31]. When the internet is down we will read, or watch, whatever we have available.

We can model this along the lines of the prey choice model from food foraging, which describes which types of prey are worth pursuing and consuming [8]. Assume an information forager is within a media environment where they are searching and encountering information of different types, \( i \), each at its own Poisson rate \( \lambda_i \). If consumed, the information provides a benefit \( u_i \) in a handling time \( t_i \), during which time the forager is not searching. Alternatively the forager can choose to ignore the information and keep searching. The forager’s choices of whether to consume or ignore information items will determine the expected total time spent searching, \( T_s \), and handling, \( T_h \), and the total utility gained, \( U \). Within these constraints, the forager is trying to optimise the expected overall rate of utility of foraging given by

\[
R_{\text{media}} = \frac{U}{T_s + T_h}. \tag{2}
\]

Here media describes the forager’s local environment, such as a media platform. Media platforms are analogous to foraging patches in optimal foraging theory. The forager’s choices of which information types to consume can be described as an information diet, \( D \). The total expected utility is \( U = \sum_D \lambda_i u_i T_s \). Similarly the total expected handling time is \( T_h = \sum_D \lambda_i t_i T_s \). Substituting in and cancelling \( T_s \), we can write the expected utility rate given a diet

\[
R_{\text{media}} = \frac{\sum_D \lambda_i u_i}{1 + \sum_D \lambda_i t_i}. \tag{3}
\]

Consuming an information item carries an expected opportunity cost of not spending that item’s handling time looking for other items, equal to \( t_i R_{\text{media}} \), and an expected utility gain of \( u_i \). To maximise

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expected utility rate a forager should therefore consume the item if the item utility rate, \( r_i \), is greater than the overall media platform utility rate, \( R_{\text{media}} \),

\[
r_i \geq R_{\text{media}}.
\]  

(4)

This diet threshold condition is a familiar result from foraging theory [8, 9, 15]. To find the optimal diet, item types can be ranked in order of \( r_i \) and added to the diet one by one until this inequality fails [9]. See the Supplementary Information for a more thorough derivation.

We can now ask which information types a forager should include in their diet, \( D \), to maximise their expected overall utility rate as a consequence of rising information prevalence, here \( \lambda_i \). For items with \( r_i < R_{\text{media}} \), increasing prevalence has no effect as they are still not included in the diet. For items with \( r_i \geq R_{\text{media}} \), increasing prevalence will mean more time spent handling these items and less time spent searching, so the overall media platform utility rate will increase,

\[
\frac{\partial R_{\text{media}}}{\partial \lambda_i} \geq 0 \quad \forall i.
\]  

(5)

Combining this with Inequality 4, increasing information prevalence will cause a rise in the criteria for diet inclusion so that higher information utility rates are needed to enter an informavore’s diet (Figure 1d). Foragers become more selective when prey is abundant [8].

We can extend traditional foraging theory to information evolution by asking how media producers will respond to this. By assuming there is some cost to media of producing more informative messages — a standard assumption underlying Zipf’s principle of least effort [32, 33] — we conclude that an abundance of information creates an adaptive pressure that drives media producers to create information with a higher utility rate.

**Proposition 1.** As information prevalence increases, information utility rates will increase.

**Competition Between Media Platforms Drives Differences Between Short and Long-form Media**

Information is not distributed evenly around the environment but is clumped in patches, which we will call media platforms. A media platform could be a newspaper, Twitter, papers on a desk, a book etc. The forager has to choose not only which information to consume within a media platform, but also which media platforms to visit. The media choice model is analogous to the information choice model in the previous section, and following that logic we find an analogous result to Inequality 4: an optimal information forager will visit a media platform if the expected media utility rate is greater than the background utility rate from foraging in the overall environment (see Supplementary Information for the full model),

\[
R_{\text{media}} \geq R_{\text{env}}.
\]  

(6)

A media platform is characterised by the types of information it contains. The utility rate of a media platform, \( R_{\text{media}} \), involves summations over separate Poisson processes (Equation 3). To simplify this, let \( \bar{u}_m \) be the average utility of information items consumed in the media platform, \( \bar{t}_m \) the average time spent consuming information items, and \( \lambda_m \) the rate of encounter of any item in the diet. Following this, equation 3 becomes a variation of Holling’s disc equation [34] (full derivation in Supplementary Information),

\[
R_{\text{media}} = \frac{\lambda_m \bar{u}_m}{1 + \lambda_m \bar{t}_m}.
\]  

(7)

Dividing the denominator by the numerator, and substituting the average item utility rate, defined as the expected utility per unit time spent handling items in the media platform, \( \bar{r}_m = \frac{\bar{u}_m}{\bar{t}_m} \),

\[
R_{\text{media}} = \frac{1}{\frac{1}{\lambda_m \bar{u}_m} + \frac{1}{\bar{r}_m}}.
\]  

(8)

This is visualised in Figure 2d. Combining Equation 8 with Inequality 6 the criteria for inclusion in an information forager’s diet is

\[
\frac{1}{\lambda_m \bar{u}_m} + \frac{1}{\bar{r}_m} \leq \frac{1}{R_{\text{env}}}.
\]  

(9)
Figure 1: a) Word entropy of text samples in the Corpus of Historical American English has risen since around 1900. This is a robust result, with similar trends in the alternative word distribution measures of b) type token ratio and c) Zipf exponent. (Timeseries are smoothed with a moving average window of ±5 years, and then averaged over media categories. Shaded region shows 95% confidence interval of this average.) This is explained by d) simulations of the information choice model with varying information prevalence. For each prevalence, information items are either in the diet and consumed (blue) or ignored (grey). At higher information prevalence, foragers are more selective with items in their diet, which increases the average item utility rate, a proxy for entropy.

The inclusion of a media platform in the information diet is therefore determined by three properties of the information items that it contains: the average utility (i.e. size) of an item, $\bar{u}_m$; the average item utility rate, $\bar{r}_m$; and the prevalence of items within the media platform, $\lambda_m$.

Short-form media platforms such as news and magazines involve more time spent switching (and searching for) articles than long-form media platforms like books. As such, in order to reach the same overall media platform utility rate, $R_{\text{media}}$, the information items themselves need to be more information dense in short-form media, to balance this extra time spent switching. In foraging terms, an animal might pursue prey which is calorie rich but small such as berries, or they might spend all day chewing grass in a field.

This creates a differential selective pressure on short- and long-form media producers. Given some $R_{\text{env}}$, the short-form media platform needs higher average information utility rates, $\bar{r}_m$, to be accepted in the forager’s diet than the long-form media. The long-form media experiences a relaxed selective pressure on information utility rates because there is less time wasted spent switching in these media platforms. This cause differences in the observed information utility rates in short- and long-form media.

**Proposition 2.** In a competitive environment, short-form media will have higher average information utility rates than long-form media.

We will investigate this proposition in the Results section by considering differences in word entropy across media categories.
Figure 2: Word entropy of long-form (fiction and non-fiction), short-form (news and magazines) and very short-form (social) media. a) Short-form media has higher word entropy than long-form media in varied corpora. For each media category, distributions are kernel density estimates cut to the data range, with quartile positions shown. b) Animals foraging for food and c) people foraging for information share a common search problem. d) The expected cumulative utility (solid line) and overall utility rate (dashed line) of foraging in a media platform depend on the properties of the information items it contains. The expected utility rate (and competitiveness) of a media platform is determined by the time spent searching (horizontal solid lines) and consuming (diagonal solid lines) information. e) Consuming short-form media involves more time spent searching for information items, so that the short-form media platforms need a higher average item utility rate (diagonal solid red line gradient) to give an overall utility rate (dotted grey line) equal to that of long-form media (blue line).

Inequality 9 includes a weaker condition for diet inclusion, \( \lambda_m u_m \leq R_{\text{env}} \). This suggests a minimal average size of information for diet inclusion given a level of information prevalence. Even if we increase the average information utility rate, \( \bar{r}_m \), to infinity, there will still be a minimal size that information foragers will tolerate within a media platform. At low information prevalence, a lot of time is spent switching between items so that foragers prefer bigger information item sizes, such as books. As information prevalence increases, less time is spent switching between information items, so that foragers will tolerate media platforms with smaller and smaller information item sizes (Figure 3), such as social media. In plain language, Twitter only works in a world with instant messages — no one would go to the library to check out a single Tweet.

**Proposition 3.** As information prevalence increases, very short-form media becomes viable.

Finally, our model also provides a way to quantify why media platforms are driven to make information more easily accessible. If a media platform can increase the prevalence of information i.e. reduce the expected search time between information encounters, \( \lambda_m \), then they can reduce the left hand side of Inequality 9 and become more competitive. This affects the utility amount term, \( \frac{1}{\lambda_m u_m} \), and so will be a particularly strong effect with short-form media (in long-form media this term is already small).
Minimum average information size, $u_{\min}$, for media platform diet inclusion for varying levels of information prevalence, $\lambda_m$. Increasing average information utility rates, $\bar{r}_m$ can increase this limit only to a point. Very short-form media platforms like social media can only capture attention in a world with high information prevalence.

can help explain the drive by media platforms to make it easier to access information and minimise clicks through things like infinite scroll, autoplay videos, notifications and apps.

## Results

### Entropy Rising in the Attention Economy

We use word entropy as our main proxy for information utility rate. We analysed the Corpus of Historical American English (COHA), a balanced corpus with text samples from the 1810s to the 2000s categorised into news, magazines, fiction and non-fiction [35]. As discussed in Methods, we analysed text samples truncated to $N = 2000$ words. We found a clear trend in rising entropy since approximately 1900 (Figure 1a). For robustness we also measured two alternative measures of lexical complexity, with similar trends found since 1900 for the type token ratio (Figure 1b) and Zipf exponent (Figure 1c).

Notably, the trends in separate media categories follow the same pattern of rising word entropy (Figure 3). We analysed the timeseries of annual averages since 1900 for each media category and lexical measure using Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Mann-Kendall (MK) tests, with 23 out of 24 tests showing significant evidence of trends at $p < 0.05$. For full results and a deeper analysis, see the Supplementary Information.

### Historical Analysis of US Publishing

We investigated the history of media publishing in America. Magazine publishing was the most interesting. Figure 5 shows the historical trend in COHA magazine word entropy alongside magazine circulation figures and important events. Magazine publishers are in a two-sided market where they sell magazines to consumers and attention to advertisers [2], with the majority of revenue from selling attention [36]. This wasn’t always the case in the US — prior to the 1890s most magazine revenue was from sales with
Figure 4: Timeseries of word entropy across media categories in the Corpus of Historical American English. For each media category, the timeseries was smoothed using an average over a window of ± 5 years. The shaded regions are 95% confidence intervals of this average. All media categories show an upward trend in word entropy from 1900.

advertising considered undesirable [36]. Towards the late 19th century, a combination of rapidly decreasing printing costs, growth in the literate population, discounts from the US postal service and the ability to target adverts to a niche readership led to a new business model to emerge in magazine publishing [36]. This new model was to sell magazines lower than the price of production, increasing circulation so that those costs could be recouped by advertising revenue [36]. Before 1893, most magazines sold for 25 cents — until a price war led to the magazines McClure’s, Munsey’s and Cosmopolitan dropping their prices to 10 cents and subsequently enjoying rises in circulation and advertising revenue [36]. The 10 cent magazines contributed to a tripling in total magazine readership from 1890 in 1905 [36], and there was a huge jump in word entropy in the same period (Figure 5).

The Audit Bureau of Circulation was created by advertisers in 1914 [36] to better measure magazine readership numbers. This quantification of attention further increased pressure on magazine publishers. Other changes included moving advertisements from the back of the magazine to alongside the main content — a move that forced copywriters to improve the appeal of the content through adding color and improving graphics [36], and we hypothesise by increasing word entropy.

Word entropy continues to rise throughout the 20th century alongside magazine circulation, with a Pearson’s correlation coefficient $r = 0.91$ ($p < 0.001$), although both rise over time so that confounding factors are not ruled out (Figure 5). After the 1890s, the biggest drop in word entropy was during the great depression when magazine circulation also fell. There is a suggestion in the data that things change around the year 2000, as magazine circulation drops but word entropy continues to rise. The rise of digital media around this time is perhaps the biggest change in publishing since the printing press so we would not expect the same trends to necessarily continue — and digital media represents a new competitive pressure which would drive word entropy rise within our model, matching the historical trend.
Concerning the other media categories, circulation numbers and competition for attention certainly increased in the 20th century, and we see a general rise in word entropy. However the time series trends do not fit quite as well alongside specific historical events as in magazine publishing. This is not unexpected as they are under less direct attention economy pressure. Fiction is interesting as it had high word entropy during the 19th century, decreasing throughout that century (Figure 4). This is partly explained by a large number of plays and scripts in COHA in this time period, which have particularly high word entropy. However even removing these documents, the fiction word entropy is still very high in the 19th century. We believe the high word entropy here, and the downward trend, are not primarily caused by attention economy pressures. There may be a connection with changes in literary fashion in 19th century US fiction from romanticism towards realism, but this is beyond the scope of this study and so we leave the question open for other researchers.

**Higher Entropy in Short-form Media**

The historical trend (Figure 4) suggests differences in entropy between media categories. We investigated this relationship further in the Corpus of Contemporary American English (COCA) and the British National Corpus (BNC), as well as social media data from Facebook and Twitter. Figure 2a shows the distribution of word entropy across different media categories. See Extended Data for equivalent figures for the other lexical measures. Within COHA (limited to 2000-2007), BNC, and COCA there were significant differences in all lexical measures across media categories (ANOVA test $p < 0.01$). Short-form media categories of news and magazines (with low $u_i$ per information type) have higher entropy (with higher $r_i$) than long-form media (with high $u_i$). The shortest short-form media—Twitter and Facebook status updates—has the highest entropy. This agrees with the implications of Inequality 9 and visualised in Figure 2e.

To our knowledge this is the first large scale quantitative analysis of differences in word entropy

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Figure 5: Historical analysis of word entropy in magazines (red dotted, times series calculated as in previous figure) with key events (pink) and US Monthly Magazine circulation (purple).
(and type token ratio, Zipf exponent) between media categories. The differences persist across different corporea, and even between American and British media. Moreover, these observed patterns are explained by our information foraging diet choice model.

Discussion

Language evolution has been shown to follow a number of principles governed by human psychology. These principles have, for example, included features of biological and cultural evolution [37, 38], learning [39], cooling by expansion [41], word formation and distribution [32], and the decay of morphological complexity [40]. Our results extend the psychological consequences on language evolution to word entropy in response to information abundance.

We use animal foraging theory to understand how competition influences information evolution. Our model describes observed empirical changes in word entropy of English both within and between media categories in response to increasing information abundance. Our analysis of historical data shows that information markets respond predictably to this increased competition. Furthermore, our model offers a simple explanation in terms of humans as information rate maximisers responding to rising information abundance. We welcome alternative explanations for the observed changes and hope to start a debate in this regard. Notably, prevailing sociolinguistic models [40] and empirical results of grammatical simplification [43, 42] would seemingly predict a decrease in word entropy of English — the opposite of what we find (see Supplementary Information).

We make a key assumption that people’s attention is captured and maintained by high word entropy text. There are empirical findings that support the idea of people’s attention being attracted to high entropy information, such as eye tracking experiments that find participant’s visual attention is attracted by information with a high Kullback-Leiber divergence [44] and high complexity [45].

Essentially we assume that people are, on average, attracted to novelty and bored by repetition. Humans choices are, of course, based on more than entropy — for example, humans respond to social cues and risk [8] — just as animals do not always maximise net energy intake but also consider other factors like macro-nutrient content and predators [8]. Moreover, information producers are not simply interested in capturing attention, but also in influence and selling ideas and services [38]. Nonetheless, just as animal foraging models have been shown to predict human behaviour in a variety of domains [14, 15, 47, 48, 49], our analyses suggest these models also extend to understanding the shape of information evolution, just as the co-evolutionary arguments of Darwin might have predicted [9].

Methods

Text Corpora and Data Cleaning

Several text corpora were investigated. The Corpus of Historical American English (COHA) has over 100,000 texts spanning the 1810s to 2000s, balanced between categories of fiction, non-fiction, news and magazines [35]. The Corpus of Contemporary American English (COCA) has over 150,000 texts from between 1990 to 2008 split equally between fiction, popular magazines, newspapers, academic journals and spoken word [50]. The British National Corpus (BNC) contains over 4,000 texts from between 1960 and 1993 including written categories of academic prose, fiction and verse, newspapers, non-academic prose and biography, other published materials and unpublished materials [51]. Fiction and newspapers are common categories across the corpora. Magazines are a common category between COHA and COCA. We grouped as non-fiction the categories of COHA non-fiction, COCA academic journals and BNC academic prose.

The text sample data was cleaned before analysis in a standard way [52]. COHA and COCA are similar formats and so followed the same procedure. For both:

- Stripped any headers not a part of the main text samples.
- Removed any XML text tags.
- Removed any sentences that contained “@” symbols. COHA and COCA randomly replace words with @ symbol in groups of ten for copyright reasons [53].
- Removed apostrophes and extra whitespace.
- Used python’s natural language toolkit (nltk) package to convert text to tokens [54].
Selected the last 2000 tokens of the text sample for processing. This avoids, as much as possible, anomalous text that sometimes appears at the start of text samples such as a contents section.

For the BNC data, python’s natural language toolkit package comes with a BNC corpus reader [54], which was used to extract tokens. The only other treatment was to remove extra whitespace and apostrophes as with COCA and COHA.

We also investigated social media. The Twitter dataset consisted of 1.6 million tweets scraped from the twitter API between April and June 2009 [55] and available online at https://www.kaggle.com/kazanova/sentiment140. To simulate a twitter feed the tweets were randomly collated to create 1000 text samples with \( N \geq 2000 \) words each. The facebook dataset consisted of status updates from 2016 from a range of 163 public accounts, available online at https://github.com/minimaxir/interactive-facebook-reactions. Non-english facebook statuses were removed. The facebook statuses were collated chronologically to simulate a news feed to produce 24 text samples with \( N > 2000 \) words each. For both, the data was cleaned:

- Removed apostrophes and extra whitespace.
- Removed any urls.
- Removed hashtags and usernames i.e. any words containing “@” or “#”.
- For the facebook data, removed any non-English statuses.
- Used python’s natural language toolkit (nltk) package [54] to convert the collated samples into a list of tokens, and the last 2000 tokens taken.

Social media statuses are by nature short and do not exist in samples of \( N \geq 2000 \) words, and lexical measures of short text samples have little meaning. We simulated feeds by collating status updates. This will naturally create text samples with high lexical diversity. This isn’t a flawed analysis — the high information density of a news feed is related to the collation of statuses and how people actually consume social media.

**Lexical Measures**

Lexical diversity can be thought of as a proxy for information density, or entropy. Lexical diversity is measured using type token ratio, unigram word entropy and Zipf exponent [56]. The lexical measures are all sensitive to sample size, which is why we used text samples of a fixed size of \( N = 2000 \) words.

Type token ratio (TTR) is the number of unique words (types) divided by the total words (tokens) in a text sample.

\[
TTR = \frac{\# \text{types}}{\# \text{tokens}}.
\] (10)

Empirical unigram word entropy, \( H_1 \), is measured using the relative frequencies of words, \( f_i \), given a set of \( W \) unique words in the text sample. We use the maximum likelihood or plug-in estimator, which has the benefit of being simple and well known. And it has been shown to correlate well with more advanced estimators [28]. There is some bias in the estimator [28] but this bias is systematic so is not too important for trend analysis.

\[
H_1 = -\sum_{i=1}^{W} f_i \log_2 f_i.
\] (11)

Words in natural language are typically approximately distributed as a power law distribution between type frequency, \( f_i \), and type rank in that frequency distribution, \( r(f_i) \) [57]. This power law is parameterised by the Zipf exponent, \( \alpha \), which describes the steepness of the distribution in log space. Maximum likelihood estimation was used to estimate the Zipf exponent [57]. This estimator has the benefit of being widely used and well known. It shows bias (as do all Zipf estimators) [58], but this bias is systematic so is not critical for trend analysis.

\[
f_i \propto r(f_i)^{-\alpha}
\] (12)

**Timeseries Smoothing** The Corpus of Historical American English (COHA) provides historical text samples across fiction, non-fiction, news and magazines categories. The type token ratio, word entropy and Zipf exponent were calculated for each text sample.
The timeseries was smoothed for plotting using a moving average with measures of text samples from ±5 years. The 95% confidence interval was calculated as the standard error of this mean calculation multiplied by 1.96 (assuming normally distributed errors). For each lexical measure, the mean was plotted for each year with the confidence interval region shaded. We only included years where we had a minimum of 10 data points within the window.

For the main composite figure (Figure 1a-c), the timeseries for media categories were combined by taking an average across the timeseries annual means for the media categories that had a value for that year. The 95% confidence interval was again calculated as 1.96 times the standard error. For each year, the standard error of the estimate of the mean, $SE_X$ was computed based on the delta method,

$$SE_X = \sqrt{\sum_{i=1}^{n} SE_i^2 / n},$$

with $n$ depending on how many media categories had values for the annual mean each year.

**Timeseries Analysis**

The results were binned into years and the median taken each year (similar results were found when using the mean). Trend analyses were carried out on these binned data between the years 1900 and 2009, the last year of data. KPSS and MK tests were carried out for each measure and media category in COHA (full results in Extended Data).

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test assumes the null hypothesis of a stationary timeseries. $p$-values below 0.05 mean that we can reject this hypothesis at 5% significance and suggest a trend. The test was applied using python’s statsmodels package [59].

The Mann-Kendall test is a non-parametric trend test [60]. The test assumes no serial correlation so that errors in one observation do not predict errors in other observations [60]. Our data is independently sampled so this is reasonable. The null hypothesis is that the data has no trend, and the $p$-value tells us the probability that the data was observed under the null hypothesis. At 5% significance we reject the null hypothesis if $p < 0.05$. The test was carried out using python’s pymannkendall package [60].

**Differences Between Media Categories**

We looked at the distributions of the lexical measures within media categories in COCA, the BNC and COHA (restricted to 2000-2007 to avoid the effect of historical changes). To test for differences between the groups we carried out ANOVA tests across categories within each corpora separately for each of the lexical measures. At 5% significance, $p < 0.05$ provides evidence that the media categories are drawn from different underlying population distributions. Each of these tests reported very small $p$-values with $p < 0.001$. The tests were carried out using python’s statsmodels package [59].

For Figure 2a, the distributions of word entropy for each media category are shown as a kernel density estimate with the bandwidth determined by the Scott rule and the density trimmed to the data range.

**US Magazine Circulation** The data for magazine circulation numbers were taken from Sumner’s “The Magazine Century American Magazines Since 1900” [36] Chapter 1, which are attributed to data originally from the Audit Bureau of Circulation. This data source does not track all US magazines, but does track well-known magazines. The data was plotted without further treatment.

**Information Diet Simulations**

For Figure 3 we simulated the information diet choice model for varying levels of information prevalence. For each level of prevalence, the first step was to randomly generate a number of information items with utility rates drawn from a uniform distribution, $r_i \approx U(20, 30)$. The total number of items drawn was proportional to the information prevalence. The information diet choice algorithm was then applied, adding items in order of $r_i$ until Inequality 4 failed. The items included in the diet were considered consumed and plotted on the figure as blue points. Items that were not included in the diet were considered ignored, and were removed from the data with 80% probability, to represent the selective pressure on these items from being unable to attract attention. The surviving items were plotted on the figure as grey points. The variables were adjusted manually to illustrate a wide range of diets.

**Data Availability**

All data generated following analysis of text samples is available at [https://github.com/chasmani/PUBLIC_information_foraging_in_the_attention_economy](https://github.com/chasmani/PUBLIC_information_foraging_in_the_attention_economy).

The text corpora data is not included in the public repository for copyright and size reasons. They are available at:

- COHA and COCA. [https://www.corpusdata.org/](https://www.corpusdata.org/)
• BNC. [http://www.natcorp.ox.ac.uk/](http://www.natcorp.ox.ac.uk/)
• Twitter dataset. [https://www.kaggle.com/kazanova/sentiment140](https://www.kaggle.com/kazanova/sentiment140)
• Facebook dataset. [https://github.com/minimaxir/interactive-facebook-reactions](https://github.com/minimaxir/interactive-facebook-reactions)

**Code Availability**

All code used to generate figures and analysis is available at [https://github.com/chasmani/PUBLIC_information_foraging_in_the_attention_economy](https://github.com/chasmani/PUBLIC_information_foraging_in_the_attention_economy)

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Author Contributions

C.P. and T.T.H. conceived and developed the presented idea. C.P. developed the mathematical model and carried out data analysis, with guidance from T.T.H. C.P. took the lead in writing the manuscript, T.T.H. and W.G. gave revisions and feedback. T.T.H. supervised the project throughout. All authors reviewed the results and approved the final version of the manuscript.

Competing Interests

The authors declare no competing interests.

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Supplementary Information

1 Supplementary Information — Linguistic Niche Hypothesis

The finding in the main paper of word entropy, and lexical diversity, rising in American English is the opposite of what might be predicted by the Linguistic Niche Hypothesis. The hypothesis makes predictions about the complexity of language morphology (e.g. I ate, la casa) and syntax (e.g. I did eat, la pequeña casa), with the assumption that complexity is balanced between the two. The Linguistic Niche Hypothesis [40] suggests that languages in large, spread out social systems tend to have simpler morphological forms, with the grammatical work instead being done through syntax [40]. The hypothesised mechanism for this is that second language learners prefer simpler forms so that complex morphological forms disappear over time [40]. A global lingua franca like English should therefore be undergoing morphological simplification, and evidence does suggest that this is the case with the regularisation of English past tense verbs [43, 42] and a loss of inflectional diversity [61]. Further work suggests that this morphological simplification should correlate with a reduction in lexical diversity as measured by type token ratio [56, 62] (or word entropy) — complex morphological forms are non-repetitive (many unique word types per word token) whilst syntactic grammatical modifiers are repetitive (few unique word types per word token). We find that lexical diversity is instead rising in American English. We suggest some possible explanations:

1. English morphology is overall becoming more complex, against the Linguistic Niche Hypothesis.
2. English morphology is becoming simpler without an increase in syntactic complexity. This would be a further refutation of the already beleaguered [63, 64] equicomplexity assumption, which states that mature languages have broadly equal grammatical complexity, balanced between morphology and syntax.
3. Lexical diversity (and type token ratio) is not a good measure of morphological complexity. The increase in lexical diversity is instead driven by more concise information and a wider, and faster switching of, contexts in written media.

The third option here aligns well with the ideas in the main paper, and is in our opinion at least partly responsible. If people are drawn towards higher utility rate information then that could drive English to be more concise and to switch contexts more quickly, which would increase type token ratio without a change in morphological complexity.

2 Supplementary Information — Prey Choice Model Derivation

In the main paper we justify the prey choice algorithm using an argument that considers the opportunity cost of spending time handling a prey versus searching in the environment. Here we derive the same result more rigorously. As in the main paper, we have information types, $i$, that are encountered with rates $\lambda_i$ while searching. Each information item, if consumed, provides a benefit $u_i$ in a handling time $t_i$, during which the forager is not searching for other items.

In the main text, the expected utility rate of foraging in a media platform is given by

$$R_{\text{media}} = \frac{\sum D \lambda_i u_i}{1 + \sum D \lambda_i t_i}.$$  \hspace{1cm} (14)

This assumes that information types are either in the diet, $D$, in which case they are always consumed upon encounter, or alternatively the items are not in the diet and never consumed. We can generalise this so that forager’s have some probability of consuming an information type upon encounter, $p_i$,

$$R_{\text{media}} = \frac{\sum p_i \lambda_i u_i}{1 + \sum p_i \lambda_i t_i}.$$  \hspace{1cm} (15)

The forager can choose the probability of paying attention to each information type, and a forager’s strategy can be defined as a vector $\mathbf{p} = [p_1, p_2, ..., p_n]$. To find the strategy that gives the maximum
utility rate we can consider each of these choices, $p_j$, independently. To find the best strategy we separate $p_j$ from the summations and differentiate

$$\frac{\partial R_{\text{media}}}{\partial p_j} = \frac{\lambda_j u_j (1 + p_j \lambda_j t_j + \sum_{i \neq j} \lambda_i t_i) - \lambda_j t_j (p_j \lambda_j u_j + \sum_{i \neq j} \lambda_i u_i)}{(1 + p_j \lambda_j t_j + \sum_{i \neq j} \lambda_i t_i)^2}. \tag{16}$$

Cancelling like terms

$$\frac{\partial R_{\text{media}}}{\partial p_j} = \frac{\lambda_j u_j (1 + \sum_{i \neq j} \lambda_i t_i) - \lambda_j t_j (\sum_{i \neq j} \lambda_i u_i)}{(1 + \lambda_j t_j + \sum_{i \neq j} \lambda_i t_i)^2}. \tag{17}$$

The sign of this does not depend on $p_j$. So if $\frac{\partial R}{\partial p_j} > 0$, $R_{\text{media}}$ will be maximised with $p_j = 1$, and otherwise with $p_j = 0$. The condition for $p_j = 1$ is

$$\frac{u_j}{t_j} > \frac{\sum_{i \neq j} \lambda_i u_i}{1 + \sum_{i \neq j} \lambda_i t_i}. \tag{18}$$

The right hand side is the rate of utility excluding item $j$, $R_{-j}$. The item should be included in the diet if the utility rate of the item, $r_i = \frac{u_i}{t_i}$, is greater than the overall rate of foraging without the item.

$$r_j \geq R_{-j}. \tag{19}$$

This is equivalent to the diet inclusion criteria given in the main paper. To find the optimal diet, one can add items in order of their utility rate until the inequality fails.

### 3 Supplementary Information — Media Platform Choice Model and Non Constant Platforms

The media platform choice model considered in the main paper is analogous to the information choice model. Media platforms of each type are randomly encountered in the environment and encountered as a Poisson processes with rates $\lambda_{\text{media}}$. We also assume that media platforms have a constant expected rate of utility, $R_{\text{media}}$, and some finite time, $T_{\text{media}}$ until the rate drops to zero, which gives each media platform a total utility, $U_{\text{media}}$. Foragers can choose to either consume or ignore a media platform upon encountering it. This model is identical to the information choice model so that we can follow that derivation and jump to the conclusion that a media platform will be included in the diet if the media utility rate is greater than or equal to the overall rate of foraging in the environment, $R_{\text{media}} \geq R_{\text{env}}$.

Media platforms, like the analogous foraging patch in ecology, in reality have non-constant utility rates. Commonly foraging patch marginal utility will decrease with time [8, 65]. This can happen as finite prey are consumed [66, 8]. For example, within a patch an optimal forager will consume the most profitable items first if they can, which then makes those items more scarce and reduces the overall utility rate in the patch as time goes on [65]. This applies equally to media platforms — one will find diminishing returns while either checking emails in an inbox or collecting raspberries in a bush. Additionally, information items themselves may degrade while being consumed, for example news articles often follow an inverted pyramid structure where the most important information is presented first, with extra paragraphs adding marginally diminishing extra information [67]. Magazines, fiction and non-fiction have their own styles and utility curves. Overall we can say that utility rates in media platforms, and information items, are not constant.

An optimal forager has to choose both which media platforms to visit and how long to spend in those media platforms. This problem was famously solved for foraging patches by Charnov’s marginal value theorem [65], which we derive here in terms of media platforms. We follow the model and derivation given by Stephens and Krebs [8]. We characterise each media platform type, $k$, with an expected utility return rate as a function of time spent within the media platform, $g_k(t_k)$. We assume that media platforms are encountered randomly with rate $\lambda_k$ as Poisson processes. The forager’s decision is now how long to spend in each media platform type, with a strategy described as $t = [t_1, t_2, ..., t_k]$ ($t_i = 0$ meaning the media platform is ignored). We can rewrite equation [7] as

$$R_{\text{media}} = \frac{\sum_k \lambda_k g_k(t_k)}{1 + \sum_k \lambda_k t_k}. \tag{20}$$
Similarly to the prey choice derivation, we differentiate with respect to the time spent in a media platform type, \( t_j \),
\[
\frac{\partial R_{\text{media}}}{\partial t_j} = \lambda_j g'_j(t_j) \frac{(1 + \sum_k \lambda_k t_k) - \lambda_j(\sum_k \lambda_k g_k(t_k))}{(1 + \sum_k \lambda_k t_k)^2},
\]
where \( g'_j(t_j) = \frac{\partial g_j(t_j)}{\partial t_j} \). Setting this equal to zero, we find the maximum \( R_{\text{env}} \) when
\[
g'_j(t_j) = R_{\text{env}} \quad \forall j. \tag{22}
\]
This is Charnov’s marginal value theorem \cite{65} and states that an optimal forager will leave a foraging patch (or media platform) when the marginal utility rate of the media platform equals the overall rate of utility from foraging in the environment. And foragers will not spend any time in a media platform if the marginal rate never reaches the environmental rate i.e. \( g'_j(t_j) < R_{\text{env}} \quad \forall t_j \). This makes sense intuitively — time spent in a media platform with rate \( g_j \) carries an opportunity cost of time not spent foraging in the wider environment with utility rate \( R_{\text{env}} \).

We can find which media platforms will be visited using the “patches as prey” algorithm \cite{8}. This is a similar algorithm to the diet choice model but with patches (or in our case media platforms) ranked in order of their maximum profitability, \( g_k(t^*_k) \). Media platform types are added to the diet one at a time, with the marginal value theorem applied to all included media platforms after adding each new media platform to recalculate the environmental utility rate. This is done with all media platform types, or until Inequality 22 fails.

How would this model of media platforms effect the conclusions of the main paper? As in the main paper, we assume that media producers have an incentive to create media that attracts and holds attention. People are still driven towards media platforms with high utility rates. If media platforms (patch) degradation occurs through consuming the most attractive items first then there would still be a selective pressure toward high utility rate information items, as this would make the media platform more attractive before degradation and keep foragers in the media platforms for longer as it degrades. And this pressure would still apply more strongly to short-form media than long-form media (due to more time switching between short-form media). The conclusions in the main paper would still follow, although the full model would be more complicated. We are confident that the conclusions would hold under any reasonable model of media platform degradation.

4 Supplementary Information — The Merged Poisson Process for Media Platforms

Here we justify using average values to describe the expected media platform utility rates, instead of summations over information types. Again, media platforms are analogous to foraging patches. We have not seen this derivation for patches before in the foraging literature, but it is relatively straightforward. The result is used in \cite{21}.

In the main text we write down an equation for the expected media platform rate in terms of the characteristics of the information within the media platform diet, \( D \),
\[
R_{\text{media}} = \frac{\sum_{i \in D} \lambda_i u_i}{1 + \sum_{i \in D} \lambda_i t_i}. \tag{23}
\]

In this model, information types are encountered as independent Poisson processes with rates, \( \lambda_i \), during time spent searching, with total searching time \( T_s \). Items have utilities \( u_i \) and handling times \( t_i \). With some simple algebraic manipulation we can write down
\[
R_{\text{media}} = \frac{(\sum_{i} \lambda_i) \frac{\sum_{i} \lambda_i u_i T_s}{\sum_{i} \lambda_i t_i T_s}}{1 + (\sum_{i} \lambda_i) \frac{\sum_{i} \lambda_i t_i T_s}{\sum_{i} \lambda_i t_i T_s}}. \tag{24}
\]

We can merge the independent Poisson processes. The rate of a combined Poisson process is equal to the sum of the rate of the independent Poisson processes, \( \lambda_m = \sum_{i} \lambda_i \) \cite{68}. 

Draft
We define the average utility of items encountered in the media platform as the total utility gained divided by the total number of items handled,

\[ \bar{u}_m = \frac{\sum_D \lambda_i u_i T_s}{\sum_D \lambda_i T_s} \]  

(25)

Similarly the average time spent handling items encountered is the total time spent handling divided by the number of items handled,

\[ \bar{t}_m = \frac{\sum_D \lambda_i t_i T_s}{\sum_D \lambda_i T_s} \]  

(26)

Substituting these relations into equation 24,

\[ R_{\text{media}} = \frac{\lambda_m \bar{u}_m}{1 + \lambda_m \bar{t}_m} \]  

(27)

We can therefore replace the media rate equation (equation 23) with averages taken over the merged Poisson process. This is a variation of Holling’s disc equation [34], considering average values.

5 Extended Data — Timeseries Trend Analysis Table

|                  | Unigram Word Entropy | Type Token ratio | Zipf Exponent |
|------------------|----------------------|-----------------|---------------|
| news             | (<0.01, 0.00)        | (0.02, 0.00)    | (<0.01, 0.00) |
| mag              | (<0.01, 0.00)        | (0.02, 0.00)    | (<0.01, 0.00) |
| fic              | (0.02, 0.00)         | (0.04, 0.00)    | (0.01, 0.00)  |
| nf               | (0.01, 0.00)         | (0.08, 0.01)    | (0.01, 0.00)  |

Table 1: Timeseries analysis across different categories and measures for text samples from COHA between 1900 and 2009. In each cell, the p-value of a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and a Mann Kendall (MK) test are shown respectively. Significant trends are emboldened. For both tests, p-values below 0.05 mean we can reject the null hypothesis of stationarity at 5% significance. Unigram word entropy and Zipf exponent show trends across all categories and both tests. Stationarity could not be ruled out for type token ratio for non-fiction by the KPSS test. See Methods for further details.

6 Extended Data — COHA Timeseries for Type Token Ratio and Zipf exponent

7 Extended Data — Corpora Distributions for Word Entropy, Type Token Ratio and Zipf exponent
Figure 6: Historical timeseries of type token ratio in the Corpus of Historical American English. Type token ratio was calculated for text samples from COHA truncated with $N = 2000$ words. For each media category and year, a moving average of all valid samples with $\pm 5$ years was calculated. The shaded region shows a 95% confidence interval for this average.
Figure 7: Historical timeseries of Zipf exponent in text samples in written media categories in American English. The timeseries was calculated in the same way as in the previous figure.
Figure 8: Distribution snapshots of type token ratio across different text corpora for text samples with $N = 2000$ words. COHA samples are from the year 2000 onwards only. Social media text samples were collated from status updates.
Figure 9: Distribution snapshots of the Zipf exponent across different text corpora for text samples with $N = 2000$ words. COHA samples are from the year 2000 onwards only. Social media text samples were collated from status updates.