Lightweight Decoding Strategies for Increasing Specificity

Katy Ilonka Gero  
Columbia University  
katy@cs.columbia.edu

Chris Kedzie  
kedzie@cs.columbia.edu

Savvas Petridis  
Columbia University  
sdp2137@columbia.edu

Lydia B. Chilton  
chilton@cs.columbia.edu

Abstract

Language models are known to produce vague and generic outputs. We propose two unsupervised decoding strategies based on either word-frequency or point-wise mutual information to increase the specificity of any model that outputs a probability distribution over its vocabulary at generation time. We test the strategies in a prompt completion task; with human evaluations, we find that both strategies increase the specificity of outputs with only modest decreases in sensibility. We also briefly present a summarization use case, where these strategies can produce more specific summaries.

1 Introduction

Language models (LMs) are known to produce vague and generic outputs (Holtzman et al., 2019). In domains like summarization (Fan et al., 2018a), dialogue generation (Yao et al., 2016), and creative computing (Fan et al., 2018b), outputs with higher specificity are often desired. While controlling the specificity of model outputs has been explored previously, it is primarily approached as a supervised learning problem where access to large, in-domain training sets are prerequisites for implementation.

However, pre-trained LMs are increasingly of sufficient quality such that only a text prompt is necessary to obtain a task specific language generator (Brown et al., 2020). It would be beneficial to control the specificity of these models’ outputs in an unsupervised manner because re-training or fine-tuning such models are non-trivial or impossible tasks—for instance because the language model is too large, only accessible by an API, or the generation task does not have training data.

To that end, we propose two unsupervised decoding strategies to increase the specificity of LMs that can work with any LM that outputs a probability distribution over its vocabulary at generation time. The first is based on word frequency and the second on positive point-wise mutual information (PPMI). We show in a prompt completion task that unsupervised reweighting strategies based on these quantities improves the specificity of generated outputs while only modestly affecting the sensibility according to human annotators.

This paper has four main contributions:1

1. We propose word frequency and PPMI based reweighting schemes of an LM’s output probability distribution to increase specificity.
2. We verify with human evaluations on a prompt completion task that these schemes improve specificity with only modest drops to sensibility. We find this holds both in deterministic and stochastic generation settings.
3. We verify with automatic measures that these schemes improve the diversity of outputs in deterministic generation settings.
4. We show how these schemes can be used to control generated summaries of news articles.

2 Related Work

Both word frequency and PPMI have been used in prior work to control the specificity of generated outputs. Yao et al. (2016) train a dialogue generation model using a supervised learning objective and reinforcement learning to maximize the inverse document frequency (IDF) of generated responses, which improves the quality of both generation and retrieval. Relatedly, Ko et al. (2019) condition a decoder on a variety of measures (including word frequency) to improve specificity in dialogue generation and find that linguistically-driven measures generate the most informative and topical responses. Zhang et al. (2018a) train a neural dialogue generation model that takes as input the text of the previous utterance but also the normalized maximum inverse word frequency of the desired

---

1Implementations and evaluations will be released after anonymous review.
response, which significantly outperforms state-of-the-art models. Takayama and Arase (2020) propose a similar approach, using maximum PPMI between utterance and response as the specificity control mechanism.

While all four works attempt to increase the specificity of generated outputs, they do so via training a language generator from scratch. Additionally, while Yao et al. (2016) only adds a loss function, Ko et al. (2019), Zhang et al. (2018a) and Takayama and Arase (2020) add purpose built neural components to the decoder to incorporate specificity controls, something that would be difficult to do with a large, pre-trained LM like GPT-3. By comparison, our proposed unsupervised reweightings do not require retraining, fine-tuning, or additional decoder modifications and can work with any LM that produces a probability distribution over next tokens. Being able to easily control specificity in such models as a light-weight post-processing step is crucial as most researchers do not have the resources to train such models from scratch.

3 Controlling Generation Specificity

We present two ways to modify the probability distribution of a LM. The first relies on normalized inverse word frequencies (NIWF), which can be easily calculated using any desired corpus and doesn’t depend on the prompt. The second relies on a calculation of positive point-wise mutual information (PPMI), which can be calculated using any desired corpus, but does rely on defining some context (likely a word or words from the prompt) for the calculation.

In either case, a corpus (which does not need to be the original training corpus) is used to modify the probability distribution coming out of the LM. Both schemes modify the original distribution by adding a token specific term \( b_t \in \mathbb{R} \) to the unnormalized log probability \( a_t, \in \mathbb{R} \):

\[
\text{(original model)} \quad \log p_\theta(t_i) \propto a_{t_i} \tag{1}
\]

\[
\text{(rewighted model)} \quad \log p_\theta(t_i) \propto a_{t_i} + b_t \tag{2}
\]

where \( p_\theta(t_i) \) is the probability under the LM of generating token \( t_i \) at step \( i \).\(^2\)

3.1 Normalized Inverse Word Frequency (NIWF)

NIWF is often used to measure specificity (Li and Nenkova, 2015; Ko et al., 2019); here we use it to calculate a modified probability for each token \( t_i \) in the model (at generation time).

Let \( n_t \) be the count of token \( t \) in a corpus and let \( n^*_t = \max_{c \in V} n_t \) be the maximum count occurring in the corpus. The NIWF reweighting \( b_t \) of a token \( t \) is then calculated as:

\[
b_t = \min \left( \max \left( w_0, \frac{n^*_t}{kn_t} \right), w_1 \right) \tag{3}
\]

where \( k \in \mathbb{R} \) is a scalar to adjust the range and \( w_0, w_1 \in \mathbb{R} \) are lower and upper bounds respectively. We set \( k = 100 \). In practice, \( \frac{n^*_t}{kn_t} \) can vary quite widely. To ensure the probability distribution of the model is not disturbed beyond recognition, we set \( w_0 = \exp(-5) \) and \( w_1 = 1 \) to bound \( b_t \) roughly between 0 and 1. The effect is that the rarest words receive an increase of at most 1 to the original \( a_t \) term while common words will receive almost no increase.

3.2 Positive Point-wise Mutual Information (PPMI)

PPMI is another measure often associated with term specificity (Takayama and Arase, 2020) and measures the positive association between two events. This reweighting requires a context event between which to compute the PPMI of the tokens from the model vocabulary. In our case let the context \( c \in \mathcal{V} \) be a set of topically related words from a prompt text we would like the LM to complete (see section 4.1 for a concrete example).

We then define the modification term \( b_t \) to be

\[
b_t = \max \left( 0, \log \frac{p(c,t)}{p(c)p(t)} \right) \tag{4}
\]

where \( p(c), p(t) \), and \( p(c,t) \) are the marginal probability of context words \( c \) occurring, the marginal probability of token \( t \) occurring, and the joint probability of context words \( c \) and token \( t \) co-occurring respectively.

These probabilities are estimated from a corpus of sentences with \( p(c,t) = \frac{n_{c,t}}{n_t}, \ p(c) = \frac{n_c}{n_s}, \) and \( p(t) = \frac{n_t}{n_s} \) where \( n_t \) is the number of sentences token \( t \) occurs in, \( n_c \) is the number of sentences the context words \( c \) occur in, \( n_{c,t} \) is the number of sentences where both a context word and \( t \) co-occur, and \( n_s \) is the size of the corpus in sentences.

\(^2\)Typically \( p_\theta(t_i) \) will be conditional on the previously generated tokens \( t_1, \ldots, t_{i-1} \) and optionally a context \( c \) but we omit explicitly stating them here since they are not necessary to explain the reweighting schemes.
Appendix A shows how these reweightings impact the log probabilities for a specific prompt.

### 4 Experiment

To test these methods, we use a science writing task where the model must produce a noun phrase about a technical topic. For instance, one prompt is “Cryptography is used by”. This task requires the LM to say something sensible, that makes sense given the topic, and specific, that doesn’t apply to just any topic. This is a difficult task for most pre-trained LMs which tend to produce very vague outputs (e.g., completing the cryptography prompt with “people” or “many”).

We use five topics randomly sampled from Wikipedia’s list of Computer Science topics: cryptography, human-computer interaction, support vector machines, databases, and data structures.

For each topic we use four prompts to generate noun phrases: “is used by”, “is used in”, “is studied by”, and “is studied in”. These prompts were selected for their ability to generate meaningful noun phrases about the topic. For each prompt we generate five output noun phrases. This setup leads to 100 statements per condition (5 topics × 4 prompts × 5 outputs) that can be scored for how sensible and specific the statement is.

We look at two generation paradigms: deterministic (beam search) and stochastic (top-k sampling). For each paradigm, we have three conditions: original model (no reweighting), NIWF reweighting, and PPMI reweighting. Additionally, for top-k sampling we also run the original model with a temperature parameter set to $\tau = 1.7$.

### 4.1 Implementation Details

We use the Hugging Face implementation of GPT-2 (gpt2-large) as our pre-trained LM. To calculate the reweighting, we use a corpus of Vox news articles, which has over 30 million tokens.

For the PPMI reweighting, we consider the context to be the tokens making up the title of the computer science topic. For the top-k sampling (Fan et al., 2018b) we set $k = 50$. To ensure outputs for each prompt are unique, we force the first token to be unique. For each prompt we generate the next 10 tokens, and use a parser to select the first noun phrase. See Appendix B for details on noun phrase selection.

### 4.2 Evaluation Methodology

We have two human annotators score each statement for how sensible and specific it is. We follow previous work on eliciting sensibility judgements from LM prompt completions (Li et al., 2016b) using a 0 – 4 scale for sensibility, where 0 is “Doesn’t make sense” and 4 is “Generally true.” We use a similar 0 – 4 scale for specificity, where 0 is "Not sure if it applies" and 4 is "Applies to this topic in particular". We calculate a weighted Cohen’s $\kappa$ to ensure adequate interannotation reliability, and average the annotators’ scores if they differ. Each annotator is a PhD student in computer science with expert knowledge of the topics. For sensibility we had an $\kappa = 0.35$ (fair agreement) and for specificity we had a $\kappa = 0.53$ (good agreement).

We also calculate three diversity measures following Takayama and Arase (2020). We report dist-1 and dist-2 (unigram and bigram uniqueness) and ent-2 (bigram-based entropy). See Appendix C for details on the diversity measures.

### 4.3 Results

The results for all measures can be seen in Table 3. We run significance tests (Mann-Whitney rank test for non-parametric data) on all conditions

---

Table 1: Example outputs for the different conditions.

| condition | example outputs for prompt: |
|-----------|-----------------------------|
| original  | beam search                 |
| NIWF      | the world’s largest companies |
| PPMI      | Telegram apps               |
| top-k sampling ($k=50$) | |
| original  | many applications           |
| $\tau = 1.7$ | many other crypto technologies |
| NIWF      | bitcoin wallet owners       |
| PPMI      | privacy advocates           |

---

4.1 Implementation Details

We use the Hugging Face implementation of GPT-2 (gpt2-large) as our pre-trained LM. To calculate the reweighting, we use a corpus of Vox news articles, which has over 30 million tokens.

For the PPMI reweighting, we consider the context to be the tokens making up the title of the computer science topic. For the top-k sampling (Fan et al., 2018b) we set $k = 50$. To ensure outputs for each prompt are unique, we force the first token to be unique. For each prompt we generate the next 10 tokens, and use a parser to select the first noun phrase. See Appendix B for details on noun phrase selection.

---

4.2 Evaluation Methodology

We have two human annotators score each statement for how sensible and specific it is. We follow previous work on eliciting sensibility judgements from LM prompt completions (Li et al., 2016b) using a 0 – 4 scale for sensibility, where 0 is “Doesn’t make sense” and 4 is “Generally true.” We use a similar 0 – 4 scale for specificity, where 0 is "Not sure if it applies" and 4 is "Applies to this topic in particular". We calculate a weighted Cohen’s $\kappa$ to ensure adequate interannotation reliability, and average the annotators’ scores if they differ. Each annotator is a PhD student in computer science with expert knowledge of the topics. For sensibility we had an $\kappa = 0.35$ (fair agreement) and for specificity we had a $\kappa = 0.53$ (good agreement).

We also calculate three diversity measures following Takayama and Arase (2020). We report dist-1 and dist-2 (unigram and bigram uniqueness) and ent-2 (bigram-based entropy). See Appendix C for details on the diversity measures.

---

4.3 Results

The results for all measures can be seen in Table 3. We run significance tests (Mann-Whitney rank test for non-parametric data) on all conditions

---

To reduce the sparsity of sentence level co-occurrence counts, for each topic context $c$ we also manually add morphologically related words (e.g. $c = \{\text{cryptography}, \text{cryptographic}, \text{cryptographer}, \ldots\}$).
Baseline generation: The Colonial Pipeline has restarted after a six-day shutdown. The pipeline’s operators warned it will take several days for service to return to normal. The shutdown sparked panic-buying and hoarding that has overwhelmed gas stations in the Southeast.

NIWF + market (economics): The Colonial Pipeline has restarted after a six-day shutdown. The pipeline was shut down after suffering a ransomware attack. It provides nearly half the gasoline and diesel consumed by the East Coast. Oil industry executives warned Wednesday that gas hoarding is worsening the supply crunch.

PPMI + ransomware attack: The Colonial Pipeline launched the restart of its operations Wednesday evening. The pipeline took itself offline Friday after suffering a ransomware attack. The shutdown sparked panic-buying and hoarding that has overwhelmed gas stations in the Southeast.

Table 2: Results for generating summaries using specificity reweightings to encourage topical outputs. Italics indicate phrases related to the selected topic.

| scheme          | sens | spec  | dist1 / dist2 / ent2 |
|-----------------|------|-------|----------------------|
| beam search     |      |       |                      |
| original        | 3.67 | 1.27  | 0.32 / 0.54 / 4.17   |
| NIWF            | 3.13*| 2.25* | 0.55 / 0.80 / 4.69   |
| PPMI            | 3.40*| 2.39* | 0.37 / 0.67 / 4.25   |
| top-k sampling  |      |       |                      |
| original        | 3.19 | 1.50  | 0.58 / 0.95 / 5.17   |
| \(\tau = 1.7\) | 3.12 | 1.51  | 0.67 / 0.98 / 5.26   |
| NIWF            | 3.35 | 2.27* | 0.70 / 0.97 / 4.98   |
| PPMI            | 3.26 | 2.27* | 0.52 / 0.87 / 4.54   |

Table 3: Results of human sensibility (sens) and specificity (spec) evaluations, and diversity measures dist1, dist2, and ent2. Best (largest) result bolded. For sens and spec, * marks significant difference from original.

compared to the original model, and report significant results when \(p < 0.001\). We found that the reweightings significantly increase the specificity scores: in the deterministic case, NIWF increased absolute specificity by 0.98 and PPMI by 1.12; in the stochastic case, NIWF increased absolute specificity by 0.77 and PPMI by 0.77. Increasing the temperature of the distribution barely increased the specificity—by only 0.01 (not significant).

Additionally, in the stochastic setting, we find that this increase in specificity actually slightly increases sensibility. The small decreases in bigram entropy (ent2) for stochastic NIWF and PPMI also suggest that the sampling distribution is more focused on topically specific words than the standard or increased temperature models.

In the deterministic setting, we saw modest, though significant, decreases in sensibility in the deterministic paradigm—NIWF decreased sensibility by 0.54 and PPMI by 0.27, a tradeoff found in prior work (Ko et al., 2019). At the same time, the automatic metrics suggest that the reweightings, especially PPMI, improve the beam search diversity which is desired in many tasks (Li et al., 2016a).

5 Use Case: Summarization

To assess the generalizability of our specificity reweightings, we apply them to summarization. In Table 2 we compare baseline summarization to generating summaries with specificity reweightings. To compute the summaries, we use the Hugging Face implementation of (pegasus), fine-tuned on the CNN Dailymail dataset. Each summary is generated from the same article on the Colonial Pipeline cyber-attack. To calculate the NIWF reweighting, we calculate word counts from the Wikipedia page on “Market (Economics)”. To calculate the PPMI reweighting, we use “ransomware attack” as our context and use the news article to obtain word and context co-occurrence counts. Both the NIWF corpus and PPMI context are hand-picked by the user.

By incorporating a specificity reweighting, the summary is more focused on the selected topic. Compared to the standard summary, the NIWF summary includes more sentences pertaining to “market”, including phrases like “supply crunch”, “gas hoarding” and “oil industry executives”. Similarly, the PPMI summary includes a specific sentence on the ransomware attack. With the reweightings, users can define a context to generate summaries focused on the topic of their interest.

6 Conclusion

We find that word frequency and PPMI based reweighting schemes increase language model specificity with modest to no decreases in sensibility. We demonstrate how these schemes can be used to control language model outputs in other tasks, like summarization.

\(^7\)https://huggingface.co/google/pegasus-cnn_dailymail

\(^8\)https://www.cnn.com/2021/05/12/business/colonial-pipeline-restart/index.html
7 Broader Impacts Statement

In this work we seek to improve the specificity of language model outputs by introducing lightweight decoding strategies. This work has both positive and negative impacts. The positive impacts include making the control of large, pre-trained language models more accessible to researchers and practitioners, as well as decreasing the compute costs (and therefore environmental and financial costs) of controlling large, pre-trained language models.

However, the use of large, pre-trained language models has been called into question given the gargantuan amounts of data they are trained on, which re-enforce hegemonic societal perspective and can introduce harm in downstream tasks (Bender et al., 2021). Making these models easier to control and use may encourage people to neglect the dangers involved with these models.

References

Emily M Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the dangers of stochastic parrots: Can language models be too big? In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, pages 610–623.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165.

Angela Fan, David Grangier, and Michael Auli. 2018a. Controllable Abstractive Summarization. In Proceedings of the 2nd Workshop on Neural Machine Translation and Generation, pages 45–54, Melbourne, Australia. Association for Computational Linguistics.

Angela Fan, Mike Lewis, and Yann Dauphin. 2018b. Hierarchical neural story generation. arXiv preprint arXiv:1805.04833.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2019. The curious case of neural text degeneration. arXiv preprint arXiv:1904.09751.

Wei-Jen Ko, Greg Durrett, and Junyi Jessy Li. 2019. Domain agnostic real-valued specificity prediction. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 6610–6617.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016a. A diversity-promoting objective function for neural conversation models. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 110–119, San Diego, California. Association for Computational Linguistics.

Junyi Li and Ani Nenkova. 2015. Fast and accurate prediction of sentence specificity. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 29.

Xiang Li, Aynaz Taheri, Lifu Tu, and Kevin Gimpel. 2016b. Commonsense knowledge base completion. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1445–1455.

Yizhe Zhang, Michel Galley, Jianfeng Gao, Zhe Gan, Xiujuen Li, Chris Brockett, and Bill Dolan. 2018b. Generating informative and diverse conversational responses via adversarial information maximization. In Advances in Neural Information Processing Systems, volume 31. Curran Associates, Inc.
A  Example Modified Probabilities

Below is a figure that shows how our reweighting schemes adjust the log probability for a specific prompt.

Figure 1: NIWF and PPMI give more weight to more specific words like ‘Bitcoin’ and ‘software’.

B  Selecting First Noun Phrase

For the experiment, which is a prompt completion task, we generate 10 tokens and then parse the entire output (i.e. the prompt and the generated text) using Spacy. To select the first noun phrase, we choose either the first noun chunk, as tagged by Spacy, or the subtree of the first noun after the third generated word, whichever is longer.

C  Diversity Measures

We follow Takayama and Arase (2020) in their definitions of \textit{dist} and \textit{ent}. \textit{Dist} (Li et al., 2016a) is defined as the number of distinct $n$-grams in the generated outputs divided by the total number of generated tokens. \textit{Ent} (Zhang et al., 2018b) considers the frequency of $n$-grams in the generated outputs, such that

$$\text{ent} = -\frac{1}{\sum_{w} F(w)} \sum_{w \in Y} F(w) \log \frac{F(w)}{\sum_{w} F(w)}$$

where $Y$ is a set of $n$-grams output by the system and $F(w)$ is the frequency of each $n$-gram. We look at all generated responses per topic in a given condition to calculate the diversity measures, and then average the measures across the five topics. We report both dist-1 (unigrams) and dist-2 (bigrams) as well as ent-2 (bigrams).

9https://spacy.io/