working title

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good to add links, but simply add these as regular citations (or footnotes)

Introduction

> *"Prompt engineering is the art of communicating eloquently to an AI."—-Greg Brockman, President OpenAI*

Prompt engineering defines the task of finding the right prompt to generate a desired output with a Large Language Model (LLM). Typically, this is an interactive and iterative process between human and LLM. There are certain writing techniques that improve the quality of the LLM's response, such as providing examples for what the desired output should look like. There are various blog posts and books (e.g. Phoenix and Taylor 2024) about how to write good prompts, in fact businesses are hiring "Prompt Engineers", even on dedicated job boards. Despite these, supposedly low-barrier, resources, end users without AI knowledge still struggle with prompt engineering (Zamfirescu-Pereira et al. 2023). Not only can prompt engineering pose a security risk, but the process is also fuzzy, hard to replicate, and might still lead to unpredictable behaviors of the model. These issues pose risks for organizations, as the obscurity of manual prompt engineering can lead to loss of know-how, and the unpredictiability of the model can lead to lawsuits, damages to brands, or missed opportunities. Problems of reproduceability, transparency, and documentation, become critical for organizations with the advent of the EU AI Act. The act requires for "High risk applications" that the AI model features, e.g. "adequate mitigation systems", "traceability of results", and, "robustness". High risk applications are common and important for society, e.g. in education, employment, and public services. Hence, measures to improve prompt engineering, which make the responses of LLMs more safe, robust and easy to document are needed.

the LLM or whatever model someone creates on top?

In this study, make a step towards safer prompt engineering, by proposing a novel type of document summary, which we call the "generative summary". The core idea of our method is, to find an input to the LLM which captures all the information contained in a focal document, as it leads the LLM to recreate this document itself. To obtain this summary, we maximize the likelihood of generating the document with a Large Language Model (LLM). Hence, these summary embeddings are optimal. To mitigate overfitting and to make these embeddings more interpretable, we also introduce a factor model to estimate these document summaries in a lower dimensional space. We show, that these embeddings capture inherent information about the document, can be used for classification as well as generation of new documents. We also find, that we can form linear combinations of generative summaries which have meaning themselves, similar to the approach by ~~Tomáš~~ Mikolov, ~~Mikolov, Ilya Sutskever,~~ et al. (2013). There is only a practical requirement for estimating these summary embeddings, namely that backpropagation of gradients is possible from the likelihood to the input of the LLM.

We apply our method to two datasets. First, an artifical dataset of advertising claims for hair shampoo and surface cleaners to validate that these generative summaries capture relevant information. In a second step, we show a marketing application of these generative summaries. We use these generative summaries to analyze market research data on product claims for a yoghurt and a yoghurt drink. We find that we can use these embeddings to capture design elements of these claims, assess the linguistic uniqueness of a claim, and represent their design patterns. Suprisingly, we find that this linguistic uniqueness is negatively

given a numerical vector of inputs (rather than textual input)

In general: I'm not yet convinced about the prompt engineering motivation. This seems a bit too far away from what we are actually doing. Would a more direct motivation work better? ==> Many (marketing) problems require the analysis or classification of text, commonly used techniques have their flaws and desiging a proper prompt to ask an LLM to do this task is difficult (and context specific). We show how an LLM can be used for this purpose.

correlated with the perceived uniqueness of an advertising claim by consumers. We explore these linguistic features and find that claims with certain words and their synonyms, cluster together, e.g. claims that emphasize the taste of a yoghurt drink or present it as a breakfast. Furthermore, we show that claims that live in certain areas of a low dimensional representation of the summary embeddings, are more likely to be rated favorably by consumers, but that small differences in wording can lead to relatively large differences in evaluation. This suggests a two-step approach to designing a market research study for advertising claims, where the first stage should focus on a wide exploration of the design space, while the second stage should focus on a fine-grained evaluation of the most promising area in this design space. We end with a sketch on how these summary embeddings can be used in an AI augmented design process, similar to applications in image data by Burnap, Hauser, and Timoshenko (2023) and Ludwig and Mullainathan (2023).

Nice!

We proceed with a brief overview of the relevant literature and introduce our methodology. After testing our procedure on synthetic data, and exploring the low-dimensional factor space for the generation of new advertising claims, we apply our model to the market research data. We conclude with managerial implications, a discussion of the limitations of our approach and expansions for this research.

Relevant Literature

how is that achieved? [the position of the embedding vector carries meaning eg. similar words are close together]

In Natural Language Processing, words, symbols, and even syllabuls are represented by so called tokens. A piece of text, represented by tokens, is what we call a document. To represent the meaning of words and phrases, rather than to just encode them by a token, we can use word embeddings. Word embeddings are numeric vectors that represent text. They are pre-trained on large amounts of text data and can capture the meaning of single words and phrases. Early approaches include the Word2Vec model by Tomáš Mikolov, Mikolov, Ilya Sutskever, et al. (2013), which we call simple word embeddings. The researchers train these word embeddings through a model that predicts the words surrounding a focal word. Thereby they learn the context in which words occurr, which is a way of representing their meaning. In this work, we use Large Language Models (LLMs). LLMs predict the next word in a sequence of words. These models, such as ChatGPT (Radford et al. 2018), generate text based on textual inputs, so called prompts. Internally, the model translates the prompt first into tokens, integer codes representing certain (sequences of) characters, and then into a lower dimensional vector representation of the text itself, which we call the input embedding. This input embedding is then passed through a neural network that yields a probability distribution over the next token in the sequence. To generate text, the model makes a draw from this distribution, and attached this generated token at the end of the prompt, repeating this process until it predicts the next token to be the end-of-text token (eos), i.e. until it predicts that the text ends. LLMs are pre-trained on large text corpora, such as the Common Crawl which contains over 250 billion pages of text. Their architecture is rooted in the attention mechanism. The attention mechanism models interactions in the text, such as negations, synonyms, or grammatical structures, across a long sequence of text. Vaswani et al. (2017) implement this mechanism in the transformer block, which is a modular building block for the neural network underlying an LLM. The combination of these transformer blocks, giant pre-training data, and huge computing resources, lead to LLMs that have "emergent capabilities". These are capabilities, which were not explicitly trained for by the developers of the model, such as the ability of a model to translate between languages, pass the BAR exam, or write textual summaries of documents (see Wei et al., n.d.; Lu et al. 2023).

pick one style for the references (and let software generate this, ideally bibtex)

is this correct? in general it will use a sequence of vectors, or not?

also topic of the text (this is attention across multiple sentences)

motivate why we think the LLM approach will be better for the generative embedding

In the following, we compare our *generative summaries* (*GS*) with three established methods to summarize documents:

- The Bidirectional Encoder Representations from Transformers (*BERT*) model's classifier token (CLS) (Devlin et al. 2018)
- Pooled word embeddings (*PWE*) (Shen et al. 2018)
- Prompt engineering approaches (*PE*) (Huang and Chen, n.d.)

perhaps explain these first if the motivation of the paper switches to summarizing text

BERT: An advanced approach to estimate a word embedding is the *BERT* model, which is a transformer based model to represent text (see Vaswani et al. 2017). Its developers have pre-trained BERT on a large

also contrast BERT to GPT (bi-directional vs one direction)

corpus of text, using two different self-supervised learning objectives. The first objective is the so called "Masked Language Model" task. Here, the researchers hide a random token in a sequence, and the goal of the BERT model is to predict which token is missing. This teaches the model the meaning of words in context. In order to learn about the information captured in a sentence, the researchers also pose the "Next Sentence Prediction" task to the model. For this training objective, the BERT model receives a pair of two sentences and needs to predict whether the second sentence follows the first one in a text. This task trains the classifier token (CLS): As it is pre-pended before every such sentence pair, it learns a representation of the information contained in the focal sentence. In practice, the output for a CLS token serves as a powerful feature e.g. for sentence classification. BERT embeddings are versatile, but can also be fine-tuned to a specific task such as text summarization. Such a fine-tuning requires the user to compile a dataset of summary-text pairs, that are representative of their application. These BERT representations are only descriptive and cannot be used for the generation of new text (see Devlin et al. 2018). There exist improvements to BERT, such as RoBERTa by Yinhan Liu et al. (2019), which improve the optimization procedure.

PWE: Shen et al. (2018) points to the value of using pooled word embeddings (*PWE*) to represent documents. The idea behind a *PWE* is that we can represent a sequence of tokens by aggregating the word-embeddings of these tokens. There are different methods we can use for this aggregation, some examples are the use of taking the average across the tokens (mean-pooling) or taking the maximum value across the tokens (max-pooling). There are various types of word embeddings that we could use for the pooling, such as Word2Vec (Tomáš Mikolov, Mikolov, Ilya Sutskever, et al. 2013; Tomáš Mikolov, Mikolov, Kai Chen, et al. 2013) or Global Vectors (GLoVe) (Jeffrey Pennington et al. 2014). These pooled word embeddings, cannot be used for text generation and perform worse than BERT embeddings in language tasks, as they do not employ the attention mechanism and loose information in the aggregation step (see e.g. Onan 2023).

for each element in the embedding vector

at this point it is not really clear why text generation is so important

PE: We can also summarize documents by passing these to an LLM and prompting the model to write a summary for us (Prompt engineering approaches, *PE*) (e.g. Huang and Chen, n.d.; Chakraborty and Pakray 2024). However, these summaries are textual, not deterministic, and their quality depends on the formulation of the prompt. For example, Liu et al. (2023) find that answers of LLMs are better, when we place relevant information at the beginning or end of the prompt, while inserting emotions into prompts also improves the quality of the LLMs response, in some cases even doubling its performance (see Li et al. 2023). Another issue is that these summaries can vary in length, and one needs to specify how detailed a summary should be. The difference in length between the summary and focal document, also makes it challenging to evaluate how much of the information of the focal document is captured by the summary (Chakraborty and Pakray 2024). If these summaries are of a high quality, i.e. represent the information in the focal document well, then they can be useful when we want to share a written summary of a document. In this paper, we propose a solution which works for data science and automation tasks, as we create a numeric representation of the document. We could use these textual summaries for generation, in the sense that we could prompt the model to generate a new document based on the summary.

??

A recent improvement to *PE* approaches is the framework proposed by Khattab et al. (2023). This framework, called DSPy, learns how to combine different prompting and finetuning techniques to improve the generated answer with respect to a pre-defined metric. They show that their discrete optimization procedure leads to better generated output compared to few-shot prompting and expert designed prompts, even when applied to smaller LLMs. Their approach is text based and revolves around generating examples of the desired output and then tuning the prompt and the LLM itself based on these examples. In spirit, their approach is similar to hyper-parameter tuning, in that it uses a type of (small) training data and a performance metric (e.g. whether the answer is an exact match to a certain label), and then adjusts the prompt and the LLM to maximize the scoring of its answer on this training set. The twist is, that the DSPy framework can perform such an hyper-parameter tuning in an automized fashion, by generating candidate prompts itself and selecting from them. Our proposed approach differs from DSPy in that we optimize in a continuous space, and that our goal is to find a numeric summary for a document, rather than to generate a good response to natural language tasks, such as question answering.

also write out

GS: In this work, we propose *generative summaries* (GS) which optimize the input prompt to an LLM, such that we obtain a desired outcome. These *generative summaries* perfectly replicate the focal document,

should?
(at this point in the paper it is not know whether we can actually achieve this)

thereby capturing all information contained in a document. These document summaries are deterministic, because we obtain them through maximum likelihood estimation and they live in continuous numeric space. We can evaluate the fit of such a document summary directly through the likelihood.

Replace by different term? Is not really well defined

Table 1: Overview of the methods to summarize documents.

Method	Origin	Reference	Deterministic?	Generation?	Type?
BERT	Next-sentence prediction task	Devlin et al. (2018)	✓	×	Numeric
PWE	Aggregation of token information	Tomáš Mikolov, Mikolov, Ilya Sutskever, et al. (2013) Shen et al. (2018)	✓	×	Numeric
PE	Emergent capability of LLM	Khattab et al. (2023); Huang and Chen (n.d.)	×	✓	Textual
GS	Maximize the likelihood to regenerate the focal document	*Proposed method*	✓	✓	Numeric

Methodology

write the method in more general terms?

Each document, in our case an advertising claim, d consists of the tokens $t_1^d, \ldots, t_T^{(d)}$.

The probability to generate the sequence $t_1, \ldots, t_T$ with the LLM when using the embedding $\boldsymbol{s}$ as an input is $p(t_1, \ldots, t_T \mid \boldsymbol{s})$. We can split this probability into conditional probabilities due to the autoregressive architecture of the LLM ~~and because we observe the target sequence~~. This provides large computational gains, as we can calculate these parts in parallel. Hence, we define the log-likelihood of the summary embedding for the target sequence as

usually lower case l is for log-lik, while L is for likelihood

$$\mathcal{L}(\boldsymbol{s} \mid t_1, \ldots, t_T) = \log p(t_1|\boldsymbol{s}) + \log p(t_2|t_1, \boldsymbol{s}) + \ldots + \log p(t_T|t_1, \ldots, t_{T-1}, \boldsymbol{s}),$$

and find the optimal summary embedding as

$$\mathbf{s}^* = \arg\max_{\boldsymbol{s}} \mathcal{L}(\boldsymbol{s} \mid t_1, \ldots, t_T). \tag{1}$$

We summarize the training process for the single summary embeddings in Algorithm 1. The summary embedding is a vector of length E, which is the same dimension as the dimension of the LLM's input embedding.

Algorithm 1 Training of Single Summary Embeddings

$i \leftarrow 0$
$\epsilon \leftarrow 0.01$
$\boldsymbol{s} \leftarrow \text{Initialization}(\cdot)$
while $True$ **do**
  $l^{(i)} \leftarrow \mathcal{L}(\boldsymbol{s} \mid t_1, \ldots, t_T)$
  $\nabla_s^{(i)} l \leftarrow \text{ComputeGradient}\left(l^{(i)}\right)$
  $\boldsymbol{s}^{(i+1)} l \leftarrow \text{Optimizer}\left(\boldsymbol{s}^{(i)}, \nabla_s^{(i)} l\right)$
  $i \leftarrow i + 1$
  if $l^{(i)} < \epsilon$ **then**
    break
  end if
end while

?? also give the formula that writes the vector s (high dim) as multiplication of weight vectors first (and next argue that this is in fact an auto-encoder)

why? discuss disadvantage of using the original dimension of the LLM

As we are interested in finding a low-dimensional sub-space, in which we can represent the D advertising claims, we use a factor model and estimate the summary embeddings for all advertising claims jointly, yielding the $D \times E$ matrix of summary embeddings $\mathbf{S}$. We restrict the degrees of freedom to F hidden factors. To implement this factor model, we create an Autoencoder with one hidden layer, that is fully connected with linear activation functions (Goodfellow, Bengio, and Courville 2016). The input data to this autoencoder is an identity matrix of dimension D. Before passing the summary embedding to the LLM, we pass these nodes into a Layer Normalization to stabilize the training process (Ba, Kiros, and Hinton 2016). Layer normalization works across the hidden nodes, rather than across the observations in a batch (batch-normalization, see Ioffe and Szegedy 2015). Thereby, it can also be used with a single observation. We illustrate this neural network representation of the factor model in Figure 1.

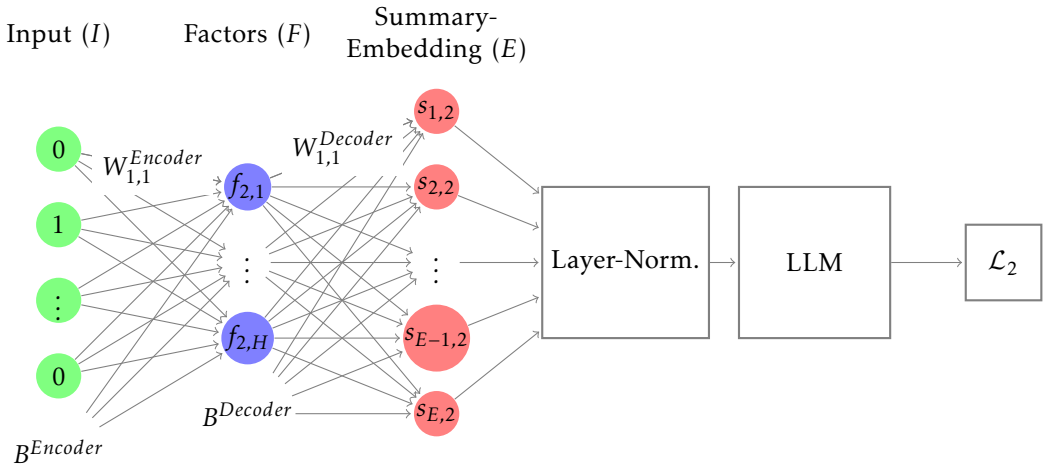


Figure 1: Factor model in Neural Network form, example for document 2

We denote the matrix of weights of the encoder and decoder layers by $\mathbf{W}^{Encoder}$ and $\mathbf{W}^{Decoder}$. These matrices have the dimensions $D \times F$ and $F \times E$ respectively. We also define the vectors of biases for the encoder and decoder by $\boldsymbol{b}^{Encoder}$ (length F) and $\boldsymbol{b}^{Decoder}$ (length E), and stack them into the matrices $\mathbf{B}^{Encoder}$ and $\mathbf{B}^{Decoder}$[1]. We denote this factor model by $\text{Factor}_{\Omega_{Factor}}(\mathbb{I}_D) : \{0,1\}^{D \times D} \rightarrow \mathbb{R}^{D \times E}$, and collect the weights and biases in Ω_{Factor}.

what do you want to say here? There is no D^2 dimensional input?

[1] We do this by taking the Kronecker product with a length D vector of ones, $\mathbf{1}_D$, to obtain the biases in matrix form as $\mathbf{B}^{Encoder} = \mathbf{1}_D \otimes \boldsymbol{b}^{Encoder}$ and $\mathbf{B}^{Decoder} = \mathbf{1}_F \otimes \boldsymbol{b}^{Decoder}$.

When we define the weights and biases in this form, we can write the factor representation of the input as

$$\mathbf{F} = \mathbf{W}^{Encoder} + \mathbf{B}^{Encoder},$$

do we need/have this?

Also write out what happens in the normalization

thereby the matrix of summary embeddings for all claims becomes

not precise enough

$$\mathbf{S} = \left(\mathbf{W}^{Encoder} + \mathbf{B}^{Encoder}\right)\mathbf{W}^{Decoder} + \mathbf{B}^{Decoder}.$$

When we estimate the matrix of summary embeddings $\mathbf{S}$, we use the joint log-likelihood to re-generate all documents in the dataset, $\mathcal{L}_D$. We estimate the summary embeddings by maximizing this joint log-likelihood with respect to the parameters of the factor model:

here the "outcome" is still the high dim vector.
We could also choose to see the low-dim vector as the output of the method

$$\mathbf{S}^* = \underset{\mathbf{W}^{Encoder}, \mathbf{W}^{Decoder}, \mathbf{B}^{Encoder}, \mathbf{B}^{Decoder}}{\arg\max} \mathcal{L}_D(\mathbf{S}). \tag{2}$$

We summarize the training process for finding the sub-space representation in Algorithm 2.

Algorithm 2 Training of Summary Embeddings based on factor model

$i \leftarrow 0$
$\epsilon \leftarrow 0.01$
$\mathbf{W}^{Encoder}_{(i)}, \mathbf{W}^{Decoder}_{(i)}, \mathbf{B}^{Encoder}_{(i)}, \mathbf{B}^{Decoder}_{(i)} \leftarrow \text{Initialization}(\cdot)$
while $True$ **do**
  $\mathbf{S} \leftarrow \left(\mathbf{W}^{Encoder}_{(i)} + \mathbf{B}^{Encoder}_{(i)}\right)\mathbf{W}^{Decoder}_{(i)} + \mathbf{B}^{Decoder}_{(i)}$
  $l_{(i)} \leftarrow \mathcal{L}_D(\mathbf{S})$
  $\nabla_{(i)} \leftarrow \text{ComputeGradient}\left(l^{(i)}\right)$
  $\mathbf{W}^{Encoder}_{(i+1)}, \mathbf{W}^{Decoder}_{(i+1)}, \mathbf{B}^{Encoder}_{(i+1)}, \mathbf{B}^{Decoder}_{(i+1)} \leftarrow \text{Optimizer}\left(\mathbf{W}^{Encoder}_{(i)}, \mathbf{W}^{Decoder}_{(i)}, \mathbf{B}^{Encoder}_{(i)}, \mathbf{B}^{Decoder}_{(i)}, \nabla_{(i)}\right)$
  $i \leftarrow i + 1$
  if $l_{(i)} < \epsilon$ **then**
    break
  end if
end while

Diagnostics

- Other methods as benchmarks
  - PWE: We create pooled word embeddings based on the Word2Vec embeddings by Tomáš Mikolov, Mikolov, Ilya Sutskever, et al. (2013)
  - BERT: We use the embedding of the CLS token which we obtain from a forward-pass through a pre-trained BERT model

(If there is time later: it would be nice to work this out in a bit more detail, this will also better show the differences)

To analyze our results, we will use a suite of diagnostic tools, which we will explain here briefly.

- Correlation matrix

low or high-dim?

  - First, we de-mean each embedding dimension by subtracting the mean of this embedding dimension calculated across observations. The motivation for this is, to take out parts of the embedding that are due to the domain of the advertising claims.

  - Correlation matrices across the claims and across the embedding dimensions: When analyzing the summary embeddings, we form correlations across the advertising claims and correlations across the embedding dimensions. The former is the same as a correlation matrix of a data matrix with as many rows as embedding dimensions and as many columns as the number of observations, while the latter is the correlation matrix of a data matrix with as many rows as observations and as many columns as embedding dimensions.

I don't get this. How can a corr matrix be not square?

and what will you do with this matrix?

- Principal Component Analysis (PCA)
  - PCA is a dimensionality reduction technique, which is rooted in the singular value decomposition. Intuitively, it projects the data onto orthogonal axes in a way that each axis captures as much variance as possible. We select the first two principal components, as this allows us to visualize our data.
  - Eigenvalue? Scree plot?

Also what to do here?
Perhaps first describe the goal/feature that you want to test.
Next how you can measure/visualize the performance

Data

in the prompt?

As a first evaluation, we create a small synthetic dataset of 20 advertising claims for a hair shampoo by querying ChatGPT with the prompt in Figure 2. We want half of these claims to advertise tangible aspects of the product and the other half to advertise intangible aspects of the product. These advertising claims all focus on how "shiny" the product ones hair makes. As as robustness check, we repeated this task for different attributes (instead of shinyness: Healthiness and colorfulness of hair), and for a different product category (surface cleaners). In total, we obtain 80 advertising claims, 20 for each of these settings. Additionally, we check whether our results are robust to changes in the order of the claims, to rule out data leakage. We show the shiny hair shampoo claims in Table 2 and moved the other analyses to the appendix.

> **Prompt:** *I work for a marketing agency. I want to market a haircare product and need some claims for this.* ***I want you to emphasize how shiny the haircare product consumers' hair makes****. I need claims that differ in style with respect to how tangible the claims are. Make these claims brief. Can you give me 10 claims that are rather tangible and 10 claims that are rather intangible?*

Figure 2: Prompt to generate the benchmark advertising claims

Table 2: Tangible (T) and Intangible (I) advertising claims for hair shampoo products.

Number	Claim
0 (T)	Experience 50% more visible shine after just one use.
1 (T)	Formulated with light-reflecting technology for a glossy finish.
2 (T)	Transform dull strands into radiant, luminous locks.
3 (T)	Infused with nourishing oils that enhance natural shine.
4 (T)	See instant brilliance with our advanced shine-boosting formula.
5 (T)	Locks in moisture to amplify hair's natural luster.
6 (T)	Achieve salon-quality shine without leaving home.
7 (T)	Visible reduction in dullness, replaced with stunning shine.
8 (T)	Say goodbye to lackluster hair, hello to mirror-like shine.
9 (T)	Clinically proven to enhance shine by up to 70%.
10 (I)	Elevate your confidence with hair that gleams under any light.
11 (I)	Embrace the allure of luminous hair that turns heads.
12 (I)	Unleash the power of radiant hair that speaks volumes.
13 (I)	Transform your look with hair that exudes brilliance.

Number	Claim
14 (I)	Feel the difference of hair that shines with vitality and health.
15 (I)	Rediscover the joy of hair that beams with inner vibrancy.
16 (I)	Indulge in the luxury of hair that shimmers with elegance.
17 (I)	Step into the spotlight with hair that radiates beauty.
18 (I)	Experience the magic of hair that dazzles with every movement.
19 (I)	Unlock the secret to hair that shines from within, reflecting your inner glow.

give some examples

For our empirical application, we obtain two datasets from a market research company. The first one contains advertising claims of yoghurt-drinks and their evaluation by consumers. The second dataset contains advertising claims for yoghurts, design motivations behind these advertising claims, and evaluations by consumers. These data stem from different variations of choice-based conjoint studies (Eggers et al. 2022), which we cannot further disclose due to confidentiality agreements. The data includes choice-experiments aggregated at the level of the advertising claims, hence we do not have responses of individuals. These measurements of consumer-preferences are on multiple dimensions, such as relevance, uniqueness of a claim, brand fit, or an overarching rating of the claim. The advertising claims were designed for markets in different countries and are in english (US, UK) or translated into english (others). The date of the study is also included in the data. Each dataset revolves around one brand.

aggregate claim evaluations

For the yoghurt drinks, we have 60 observations, 20 for each country (Germany, UK, Spain). Many of the researched advertising claims occur in multiple of these separate studies. In total, we have 26 unique advertising claims for yoghurt drinks. Most of these advertising claims get a uniqueness measure around 5.8, with the whole distribution ranging from 4.8 to 7.4. When we look at the uniqueness measure with respect to the country in which the study was held, we see that the variance is the smallest for the German market and the largest for the spanish market. However, the means are not statistically different across the countries. The distribution of the rating measure is similar in shape, ranging from 43 to 80. The rating and uniqueness are positively correlated (correlation of 0.8843). The scale for the uniqueness measure is from 0 to 10 and for the rating measure from 0 to 100. The yoghurt drink advertising claims are similar to these synthetic claims:

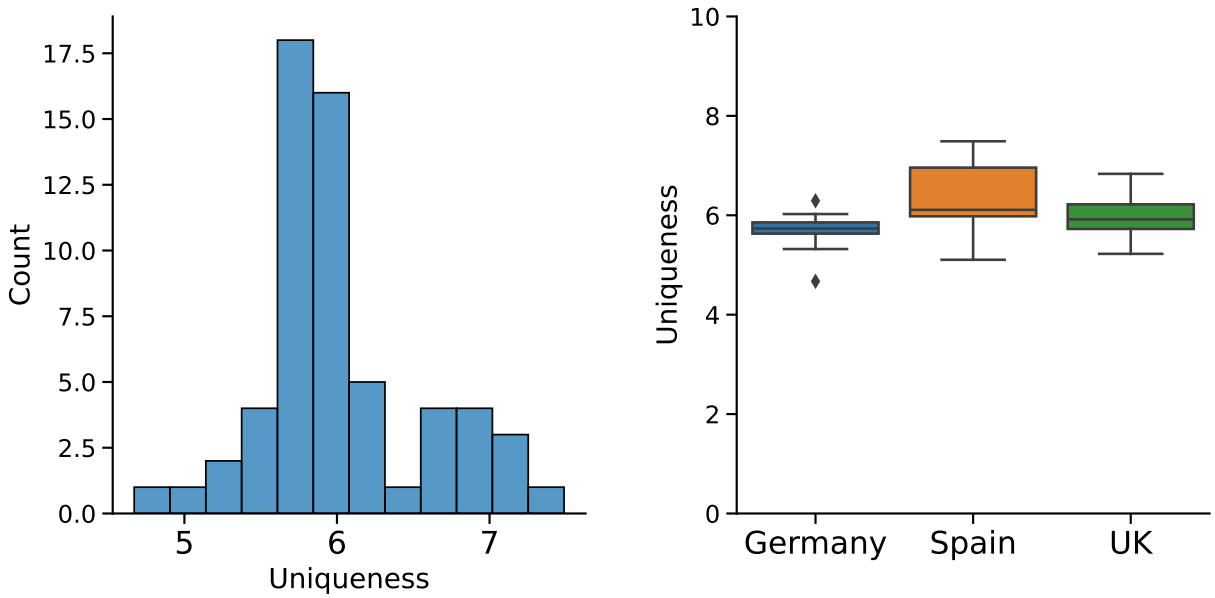
in principle on a 10 point scale?

100 point scale?

- *"A burst of fresh flavor to energize your morning"*
- *"Refresh your day with a lively new taste"*
- *"Dynamic flavor for an invigorating start"*
- *"Begin your day with a crisp and revitalizing taste"*
- *"Revitalize your senses with a pure, fresh flavor"*

For the advertising claims of yoghurts, we have 215 observations of 82 unique advertising claims. The data stems from studies in the UK, France, Germany, Spain, and Sweden. This data also contains a design motivation for the advertising claims. In total, there are 44 different classes for these design themes. We focus on the five largest classes: "Packaging", "Local & Responsible", "Sourcing", "Sustainability", and "Naturality", which account for 70% of the observations. Below, you can find a short description of what these themes look like:

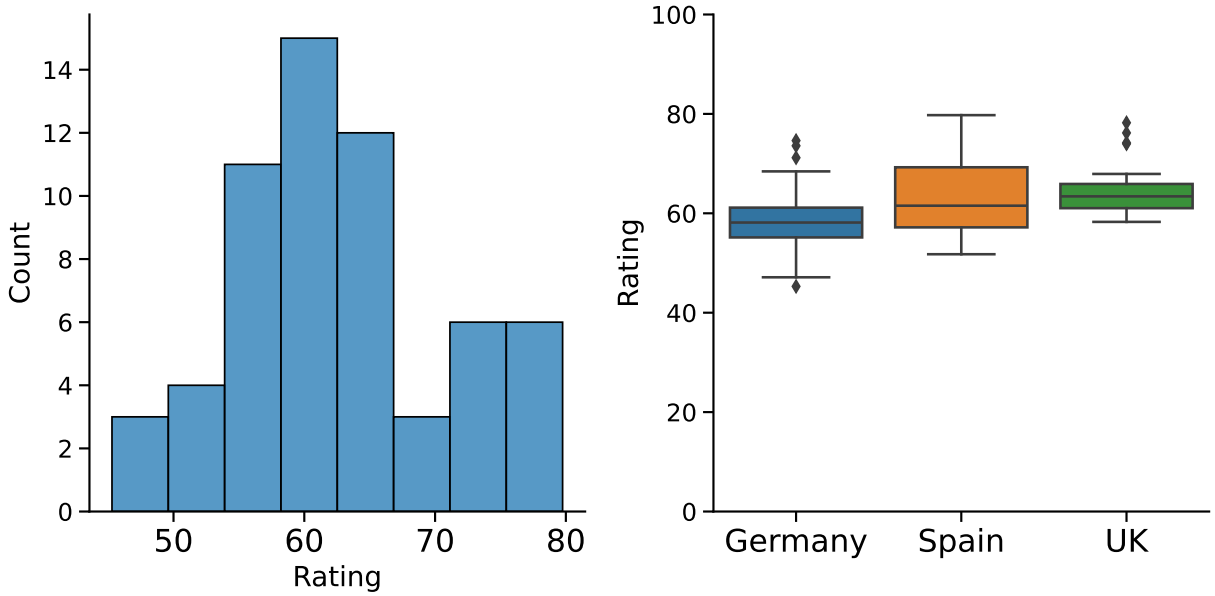
- **Packaging**: The advertising claim emphasize e.g. that the packaging is recyclable or made from eco-friendly materials
- **Local & Responsible**: The claim talks about the local origin of the yoghurt or how the yoghurt company supports local farmers
- **Sourcing**: The claim emphasizes the origin of the ingredients
- **Sustainability**: These claims state that the yoghurt is e.g. climate friendly
- **Naturality**: These claims state that the yoghurt is e.g. made from natural ingredients or has been processed as little as possible



make more clear what is in the plot itself

(a) Histogram across countries (b) Boxplot per country

Figure 3: Distributions for the claim uniqueness across the whole sample and as a boxplot per country.



(a) Histogram across countries (b) Boxplot per country

Figure 4: Distributions for the appeal rating across the whole sample and as a boxplot per country.

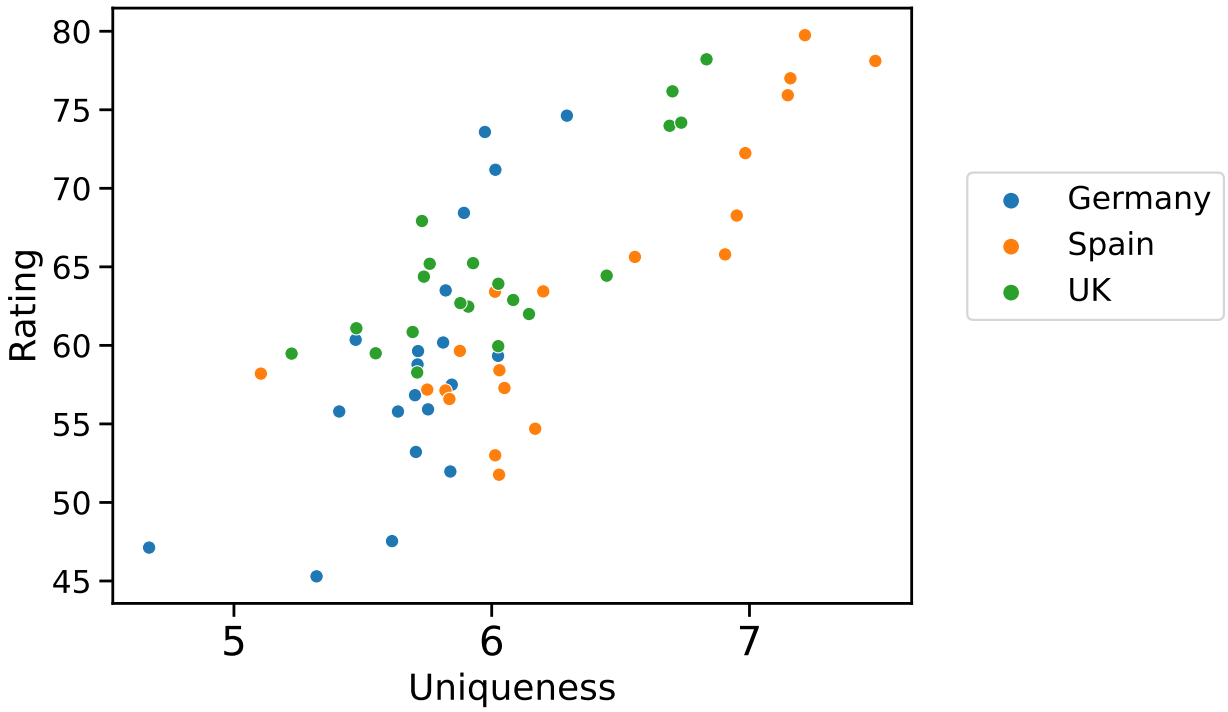


Figure 5: Scatterplot of uniqueness and rating , colored by country.

Results

For this project, we obtained a SURF NWO Small Compute Grant. We train these summary embeddings until we obtain a likelihood to generate the target claim of 0.99. We use the Adam optimizer (Diederik P. Kingma et al. 2014) with a learning rate of 0.1, no weight decay, and the values of 0.9 and 0.999 for the exponential decay rates of the first and second moment respectively. To initialize our summary embedding and factor model, we use the standard initialization of PyTorch. WE train on a Nvidia A100-GPU, which takes about 30 seconds for all 20 claims. The training of the factor representation with 2 factors and for the same claims is more computationally intense and takes about 60 minutes on the same computer. Here we traing for a joint likelihood of 0.99. We always verified that the summary embeddings regenerate all focal claims correctly. Figure 6 shows the training process for the summary embeddings estimated with the 2 factor model, the y-axis shows the negative log-likelihood (a value of 0.01 corresponds to a likelihood of $e^{-0.01} = 0.99$). Despite our efforts to mitigate spikes, we still see some smaller spikes in the tail of the optimization.

meaning that the product over all claims equals 0.99?
x^20 = 0.99
x = 0.9995

So in the second we are much stricter, this may explain a difference in computation time

from the method part it was not clear that you see this as two (competing) methods.

Also here it now seems that the factor part builds on the results of the "non-factor" model

elaborate a bit on what causes this (and what you have tried)

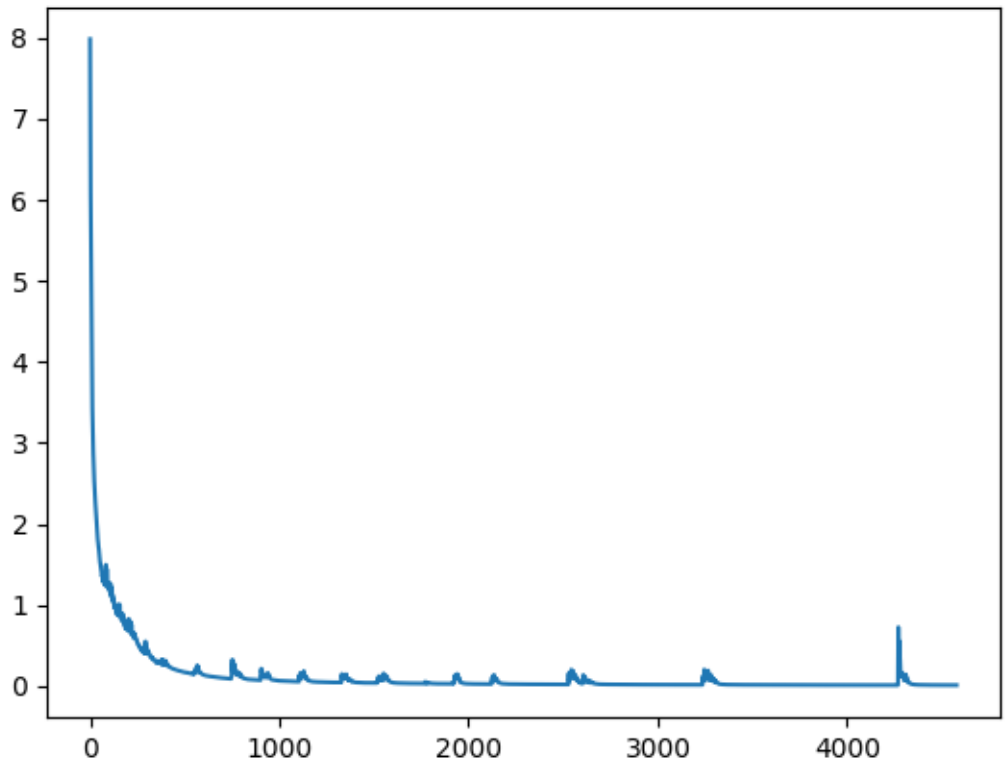


Figure 6: Training of embeddings

we show (not common to directly address the reader)

In the following, we present three versions of our summary embeddings: The single estimations, which estimates the summary embeddings for each claim separately and without the factor structure (compare Equation 1), and two factor models with 2 factors each (compare Equation 2). One of these uses the Layer Normalization, while the other one does not. We present these three versions, to illustrate the effects of the factor structure and the layer normalization. In the appendix, you can find the same diagnostics for other datasets, such as advertising claims for hair shampoo that emphasize how healthy/colorful the hair becomes (instead of shinyness), as well as for a surface cleaner that emphasize how shiny it makes surfaces. These results are robust to changing the order of the claims in the dataset.

If our generative summaries capture relevant information in the advertising claims, then we can separate between the tangible and intangible advertising claims. All claims are about hair-shampoo and shinyness. To be left with only the difference due to being tangible or intangible we demean the embeddings across the embedding dimensions (compare **mikolovDistributedRepresentationsWords2013?**). We then calculate the correlation matrix across the claims and across the embedding dimensions. When visualizing these correlations across the claims, we expect the first quartile and the third quartile of the matrix to contain positive correlations, since these are the correlations between the tangible and between the intangible claims. On the contrary, the second and the fourth quartile should contain negative correlations, since these are correlations between the tangible and intangible claims.

refer to upper-left, lower-right etc

In Figure 7 we present these correlation matrices for our GS method and the PWE and BERT approaches. Identifying these two classes works for the generative summaries which we estimate with 2 factors and layer normalization. When we compare this version to the PWE and BERT approaches, we see this pattern for all methods, indicating that all four methods are able to capture this part of information in the advertising

well

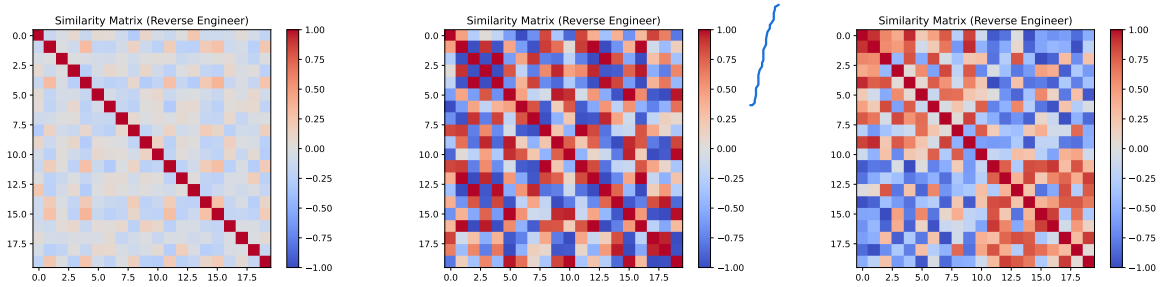
why do we need the normalization?
what is the intuition?

how can we decide on this number?

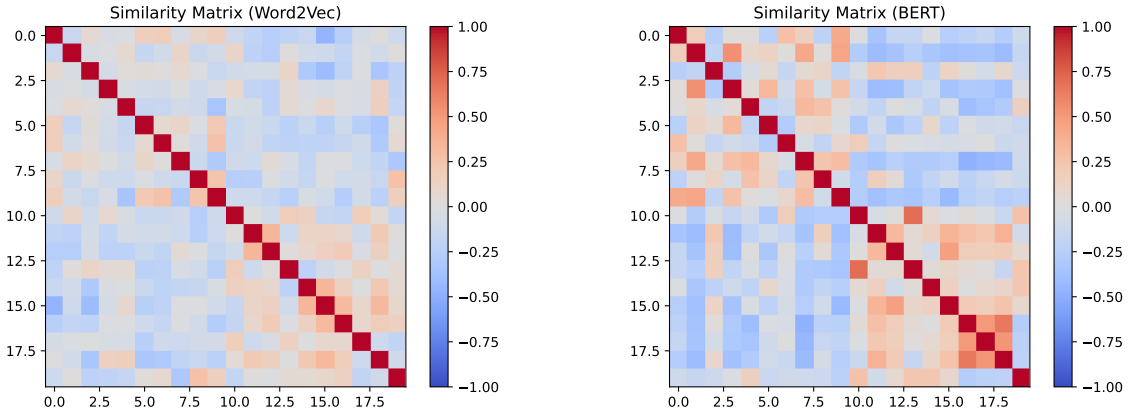
claim. We observe, that the correlations are the largest (in absolute value) for the summary embeddings and only a few correlations are close to zero. In the appendix, we show the claim correlation matrices for our other generated datasets. The results mirror the results for the hair shampoo claims that emphasize the shinyness of the hair, with one exception: The hair shampoo claims that are about how colorful it makes the hair. Here, we find that 2 factors are not enough to separate between tangible and intangible claims. We can recover these two classes by using a 15 factor model instead. Here we also observe, that the correlations are then weaker, as these document embeddings have more degrees of freedom in how their values come to be.

this is quite many

what is really represented by the correlation? (in a math sense)



(a) GS: Single estimation (b) GS: 2 Factors (c) GS: 2 Factors with LayerNorm.



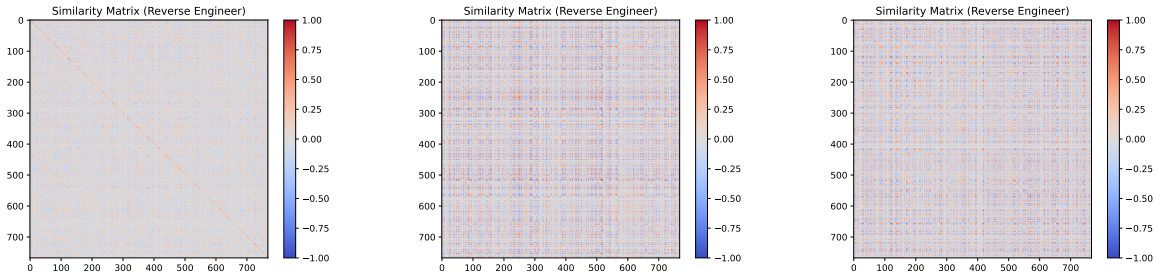
(d) PWE (e) BERT

Figure 7: Correlation matrices along the claims.

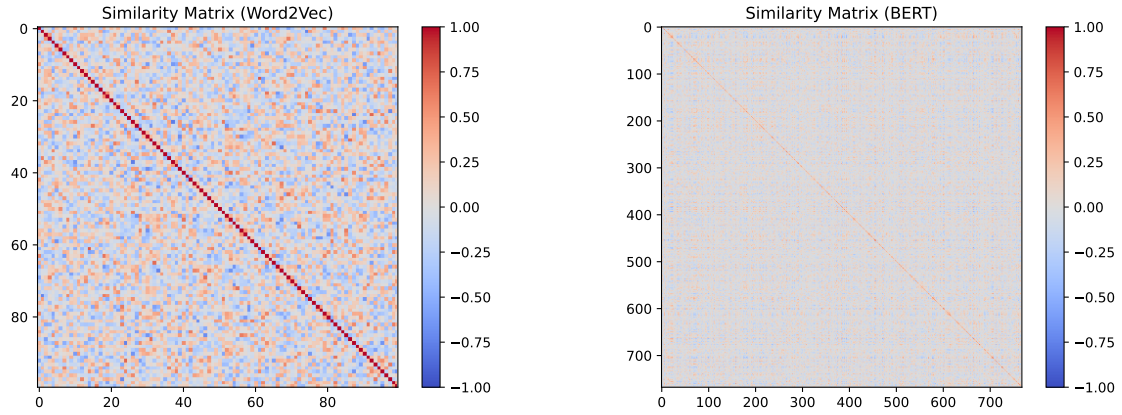
I find this terminology to be a bit confusing (does this reduce to demeaned inner products?)

Figure 8 shows correlation matrices across the embedding dimensions and illustrates the effects of using a factor structure on the summary embeddings. Each cell shows the correlation between two embedding dimensions calculated across the 20 advertising claims. When comparing our generative summaries with the twp benchmarks, we can see a stronger grid pattern with more correlations that are removed from zero. This stems from our factor structure, as this pattern is not present in the single estimation version. Making many of the embedding dimensions linearly dependent strengthens the correlations between them. In contrast, for the BERT embedding most dimensions are barely correlated with each other. The Word2Vec embedding only has 100 dimensions, as opposed to the 768 dimensions of our generative summary embeddings and the BERT embedding. Its correlations appear to be stronger, but do not exhibit the same grid pattern as for the summary embeddings.

add what this intuitively measures



(a) GS: Single estimation (b) GS: 2 Factors (c) GS: 2 Factors with LayerNorm.



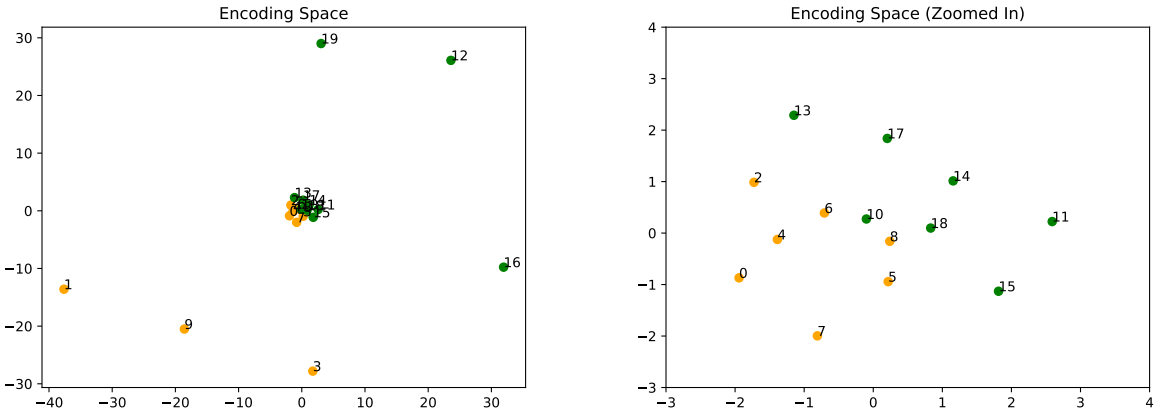
(d) PWE (e) BERT

Figure 8: Correlation matrices along the embedding dimensions.

almost(?) perfect separation!

After establishing, that our summary embeddings capture similar information to established document summary techniques, we want to explore the low-dimensional factor space of our model. Figure 9 shows the low dimensional sub-space in which we located the advertising claims, which we color in orange (tangible claims) and green (intangible claims). The assigned numbers correspond to the number of the claims in Table 2. It appears that we pick up the class with the two hidden factor, however, the classes are not directly aligned with one of these axes. Many of the points are close to zero, with a few of the claims being far removed from the other points, e.g. claims 1, 3, and 9 for the tangible, and claims 12, 16, and 19 for the intangible claims. When comparing distances in the encoding space, we can find some patterns that relate to the types of words that are used in the advertising claims. For example, the triangle of the claims 0, 4 and 7 uses words related to vision ("… visible …", "See …", and "Visible …"), and the two claims 2 and 13 both start with the word "Transform." The tangible claims far removed from the center, claims 1, 3, and 9, have in common that they talk about a form of "technology", where claims 3 and 9 both use the phrase "enhance […] shine". For the intangible claims, the two claims 12 and 19 both start with the close words "Unleash" and "Unlock". However, there are also structures in this representation which are not intuitive. We would anticipate that claim 4 would have been close to these 3 points, as it is about an "advanced shine-boosting formula", or that claim 16 ("Indulge in the luxury of hair that shimmers with elegance"), would be part of the cluster at the center, because it is similarly constructed as the 7 intangible claims there (*Feeling/Experience of the consumer-"of hair that"-feature of the hair*).

is this rotation identified in the method?
(I guess not) We can rotate this figure any way we want



(a) All points

(b) Zoom-in

Figure 9: Two dimensional factor space of the advertising claims. Numbers correspond to the numbers in Table 2, orange points are tangible claims, green points are intangible claims.

If our generative summaries indeed maximize the likelihood to generate the target text, then they also drive the chance to generate any other token towards zero. We explore the generation based on our generative summaries deeper, by analysing the generation with the generative summary. We expect that at each generation step, the probability for the correct token approaches one, while the probability for all other tokens goes to zero. In Figure 10, we visualize the next token probabilities at each generation step for correct token. We see that indeed the probability for the correct token is close to one, with the first token having the lowest probability to be generated correctly across all claims. An explanation for this is, that here, the generation relies on the generative summary alone. At later stages, the joint information of generative summary and previously generated tokens helps the generation.

it seems that all start at about 0.98. If this is the case the lik per sequence cannot exceed 0.98 and the total likelihood will be below 0.98^20 which is 0.668. This does not seem to match the target value of 0.99

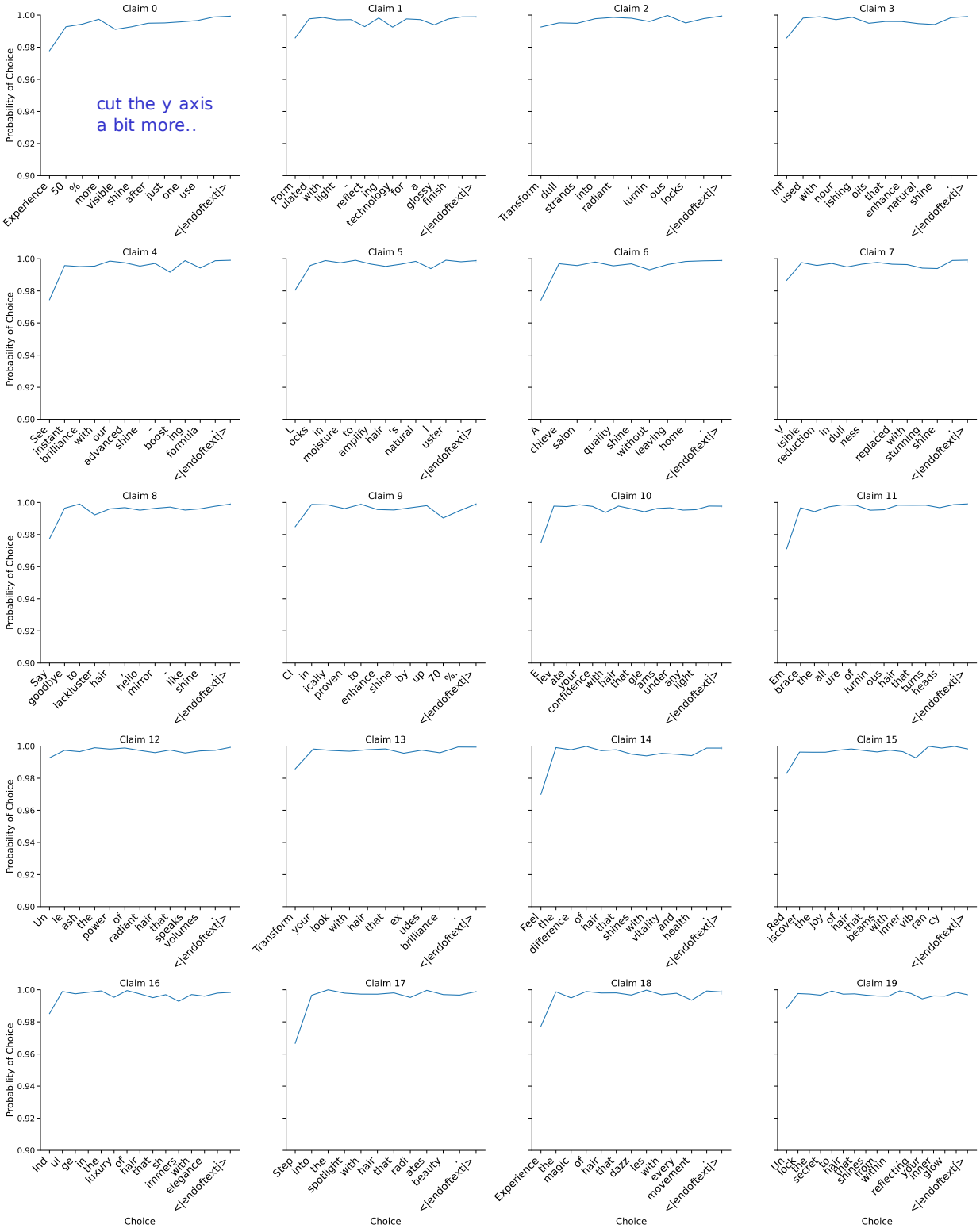


Figure 10: Conditional generation probability for the most likely token at each step. All tokens match the target claims. For the 2-factor model?

Next, we explore also the generation probability for the 2nd and 3rd most likely token at each position,

to get a better understanding of the distribution at each step. We present two examples. One for the generation of the claim with the lowest probability to correctly generate the first token, in Table 3, and another example that illustrates how we benefit from the LLMs pre-training, in Table 4. Both tables show these generation probabilities for the three most likely tokens at each generation step. Table 3 again shows how the critical step in the generation is the first token of the sequence, as the probability to generate the correct token in the second position jumps for 0.8876 to 0.9925 and never drops lower than 0.9875 again. In Table 4, we see that the most likely alternatives to the first token, "Experience", are "Form" and "See". These are words which are quite similar in how the word "Experience" is used in advertising claims. We find similar examples for the second token (1st Choice: "50", 2nd Choice: "25", 3rd Choice: "20") and the fifth position (1st Choice: "visible", 2nd Choice: "protective", 3rd Choice: "shine"). The fact that these tokens get the second and third highest generation probabilties is likely due to the pre-training of the LLM, and reflects how these words tend to be used in similar situations, such as in shampoo product claims.

Table 3: Example for a low 1st probability

	3rd	2nd	Choice	Prob. 3rd	Prob. 2nd	Prob. Choice
0	Feel	Un	Step	0.0287145	0.0344409	0.887634
1	onto	back	into	0.000927151	0.00125316	0.992544
2	to	class	the	5.98035e-05	6.91189e-05	0.99934
3	’	sun	spotlight	0.000623843	0.00123234	0.992407
4	into	in	with	0.00192485	0.00199383	0.992454
5	a	hairs	hair	0.000946804	0.000969693	0.995565
6	above	.	that	0.000743194	0.0014022	0.993072
7	X	can	radi	0.000538268	0.00169703	0.992411
8	ating	ats	ates	0.000915091	0.00206985	0.996706
9	heat	into	beauty	0.00111988	0.00228065	0.987492
10	).	.)	.	0.000529124	0.00114012	0.996219
11		]	*eos-token*	0.000603324	0.00100365	0.995909
12	*linebreak*	*linebreak*	*eos-token*	7.61097e-06	0.00124311	0.99872
13	*linebreak*	*linebreak*	*eos-token*	2.16886e-05	0.000565556	0.999231
14	*linebreak*	*linebreak*	*eos-token*	3.80865e-05	0.00084979	0.998713
15	*linebreak*	*linebreak*	*eos-token*	5.16162e-05	0.00161664	0.997724
16	*linebreak*	*linebreak*	*eos-token*	0.000101122	0.0031923	0.995816

Table 4: Example for similar tokens

	3rd	2nd	Choice	Prob. 3rd	Prob. 2nd	Prob. Choice
0	See	Form	Experience	0.00921188	0.013993	0.943786
1	20	25	50	0.00203264	0.00445767	0.976235
2	%.	.	%	0.00142157	0.00205115	0.994173
3	better	More	more	0.000946993	0.00160339	0.996037
4	shine	protective	visible	0.00178126	0.00218073	0.979003
5	glow	light	shine	0.000826363	0.00209097	0.983356
6	when	by	after	0.00171736	0.00367565	0.987
7	a	well	just	0.000570301	0.00172336	0.98959
8	two	a	one	0.00153683	0.00186334	0.989587
9	shine	usage	use	0.000427258	0.00324287	0.990624
10	,	!	.	0.000354906	0.000630647	0.9981
11	.		*eos-token*	0.000454232	0.00156762	0.994366
12	Transfer		*eos-token*	0.000179846	0.00032993	0.998234
13	*linebreak*	More	*eos-token*	0.000109437	0.000194042	0.998748
14	More	*linebreak*	*eos-token*	7.64376e-05	0.000174342	0.999236

	3rd	2nd	Choice	Prob. 3rd	Prob. 2nd	Prob. Choice
15	Lab	*linebreak*	*eos-token*	5.29115e-05	0.000444251	0.998936
16	Lab	*linebreak*	*eos-token*	0.000276325	0.00155492	0.997141

A key property of the proposed generative summaries are that we can use them for the generation of text. Can we move between to documents by interpolating their generative summaries? Table 5 shows the texts that we generated for a convex combination of the claims *"Unlock the secret to hair that shines from within, reflecting your inner glow."* (A) and *"Rediscover the joy of hair that beams with inner vibrancy."* (B), based on their generative summaries, which we estimated directly. We combine them as $\boldsymbol{s}_{combine} = weight * \boldsymbol{s}_A + (1 - weight) * \boldsymbol{s}_B$, where $weight \in [0, 1]$. For weights that are close to either 0 or 1 we still generate one of the two claims. When we step further into the middle between these two summary embeddings the end of the sequence changes first (e.g. *"Unlock the secret to blackened nails that shine from the shine."* at for $weight = \frac{3}{20}$). For weights that are close to $\frac{1}{2}$, we stop generating eos-tokens and the generated strings become unintelligble. However, these strings still maintain some of the structure of the focal claims such as having words related to beauty products and starting with the syllable "Un" or "Red".

everywhere you need to make clear which results are used (also in the tables)

Table 5: Interpolation between two advertising claims.

	Weight	Generated String
0	0/20	Unlock the secret to hair that shines from within, reflecting your inner glow. *eos-token*
1	1/20	Unlock the secret to hair that shining from within, your bedroom. *eos-token*
2	2/20	Unlock the secret to black metal's glow. *multiple eos-token*
3	3/20	Unlock the secret to blackened nails that shine from the shine. *eos-token*
4	4/20	Un to of for the team members upon Moderation of the, that
5	5/20	Un to (93) of 15 + 18 + 36 Add to
6	6/20	Un to (mit. of private eye and nirvana-ly-ly
7	7/20	Uncle-healedered with a lifetime-changing blend of light and energy and
8	8/20	Unclelyed by the Tone's Bright Side™ Lipstick. Bright
9	9/20	Unclelying our clients and fory, we're sure about your smile.
10	10/20	Redmates on the Road to of Dreams. Inspirating your soul with
11	11/20	Redmates at the Sunlight Your Hair. *multiple eos-token*
12	12/20	Redhs founder, that a master the way she loves.....
13	13/20	Redhs founder, of where, at, and to and to, and can be
14	14/20	Rediscover the joy of purpose and detail with a strand of your hair. (and
15	15/20	Rediscover the joy of success with long,istry's health and creativity. back to
16	16/20	Rediscover the joy of hair that loves to making you.™ the way.br
17	17/20	Rediscover the joy of hair that's at the-corrects life with a healthy
18	18/20	Rediscover the joy of hair that beams with inner vibrancy. *eos-token*
19	19/20	Rediscover the joy of hair that beams with inner vibrancy. *eos-token*

It appears that we can interpolate between two directly estimated generative summaries. Next, we want to explore the encoding space of a factor model and generate new texts from points in this encoding space. In Figure 11, we perform a grid search across the factor space of our 2-factor model for shiny hair shampoo claims. For each point in the grid search, we generate a text by passing this point through the decoder to create a generative summary embedding. We then pass this generative summary into the LLM to generate a text for this point from the encoding space. In the plot, we have three types of different markers. A blue bubble with a number represents the location of the respective claim, while a colored dot represents a point

where we generate one of the points that are part of the training data. Red crosses are points from which we generate a string, that comes to an end with the end of text token and is not part of the training data ("candidate points"). Whitespace represents points where we do not generate a string that comes to an end within the number of tokens that we consider. Around each advertising claim, we find an island of points from which we can generate the same claim. The islands are surrounded by candidate points, areas which are further removed from any of the training claims tend to be whitespace.

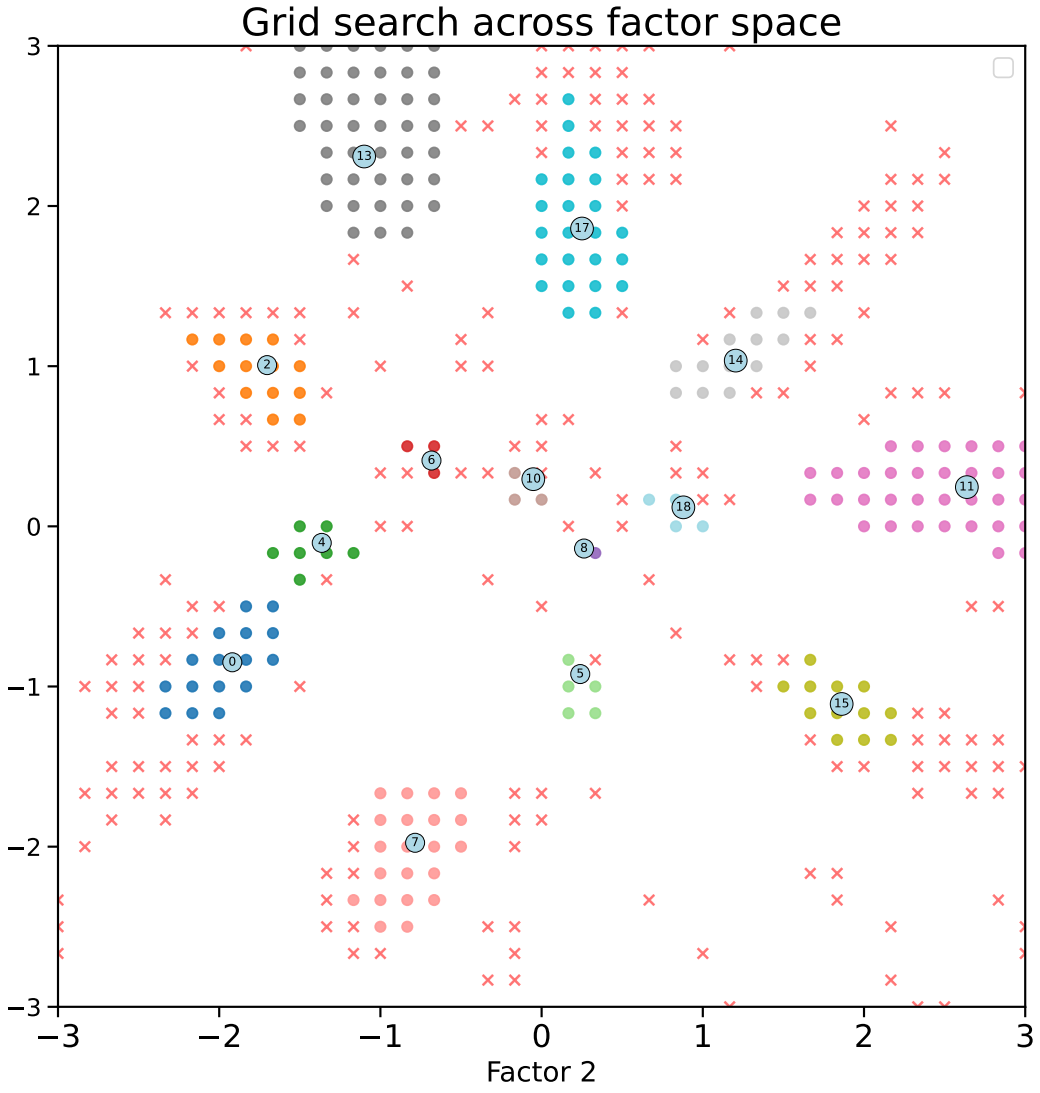


Figure 11: Exploration of Encoding Space. Numbered bubbles are the locations of the respective claim, red crosses represent candidate points. These are points from which we generate a text that ends with the eos-token, but is not part of the training data. Points that do not generate an eos-token are marked by whitespace.

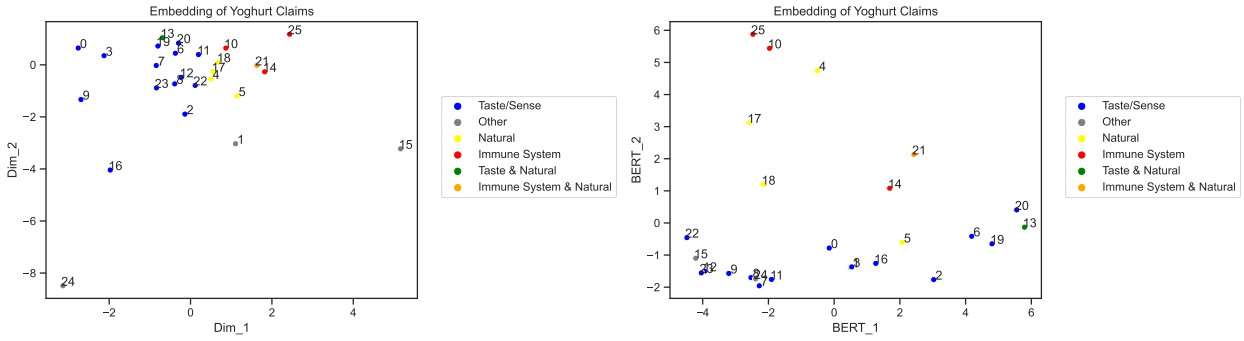
Empirical Application

Good that you already have these results!

Since we cannot disclose the actual advertising claims, we generate a set of similar claims with ChatGPT or use "stand-ins" for advertising claims, which are supposed to represent these and their properties without actually disclosing them. However, we performed all computations on the actual data. In the following, we look at two empirical application of our generative summaries. The first application is on product claims for yoghurt drinks and their appeal to consumers from three different countries. In the second application, we analyze product claims for yoghurt. For this dataset, we also have design motivations behind these product claims, which we will use to validate whether our algorithm captures these design motivations.

Yoghurt-drink claims, word features, and consumer ratings (Application 1)

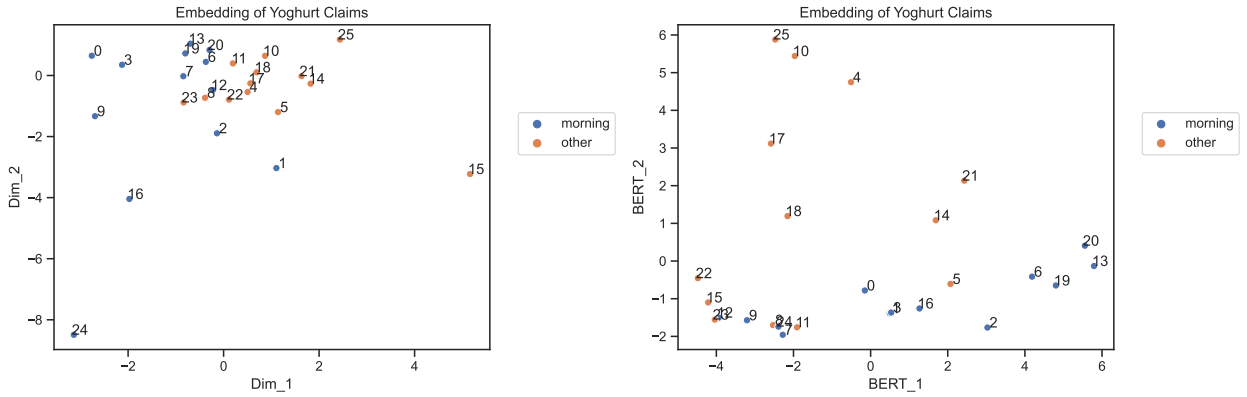
Besides the advertising claims themselves, we also have measures on the uniqueness of a claim (as perceived by consumers) and an overarching appeal rating of the claim by the consumer. To aid the market research process of finding the best advertising claims, we investigate the encoding space of the advertising claims, as estimated with a 2-factor summary embedding. First, we explore this space, in order to identify linguistic features of the advertising claims. These are not features which were reported in the data, but rather features that we interpret ourselves by looking at claims that are close to each other in the encoding space. We look at both word features (i.e. a certain word occurrs in the claim) and a higher level theme of the claim, e.g. whether the claims frames the yoghurt drink as a "breakfast" or "start in the day" ("morning" theme). Next, we are interested in whether the uniqueness measure is positively correlated to distance of claims to each other in the encoding space. Namely, whether more unique claims are more separated from other claims in the encoding space. Finally, we explore whether certain regions of the encoding space are associated with higher appeal ratings. We trained this 2-factor document summary until we reached a joint likelihood of 0.99, which training took around 8 minutes on the A100 GPU. To have a contrast to our results, we also embedd these advertising claims by summarizing them with BERT's [CLS] token and extracting the first two principal components from the resulting embedding matrix (see Pearson 1901). We want to caution, that these findings are based on a very small sample and are supposed to serve as a proof of concept on how these summary embeddings, no here their encoding space, can be useful in market research.



(a) Document Summaries

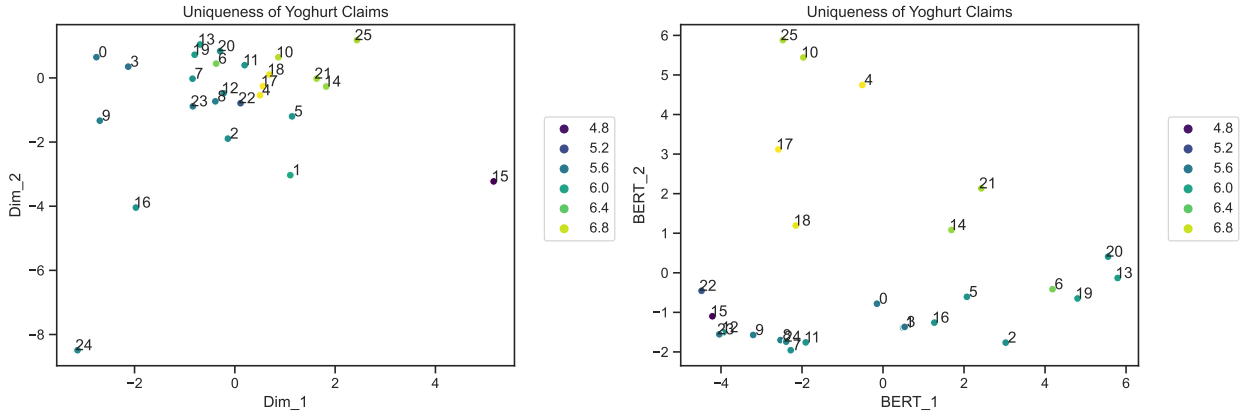
(b) BERT CLS + PCA

Figure 12: Embedding of the yoghurt claims, colored by word features.



(a) Document Summaries (b) BERT CLS + PCA

Figure 13: Occurrence of words relating to morning theme in the low-dimensional spaces.



(a) Document Summaries (b) BERT CLS + PCA

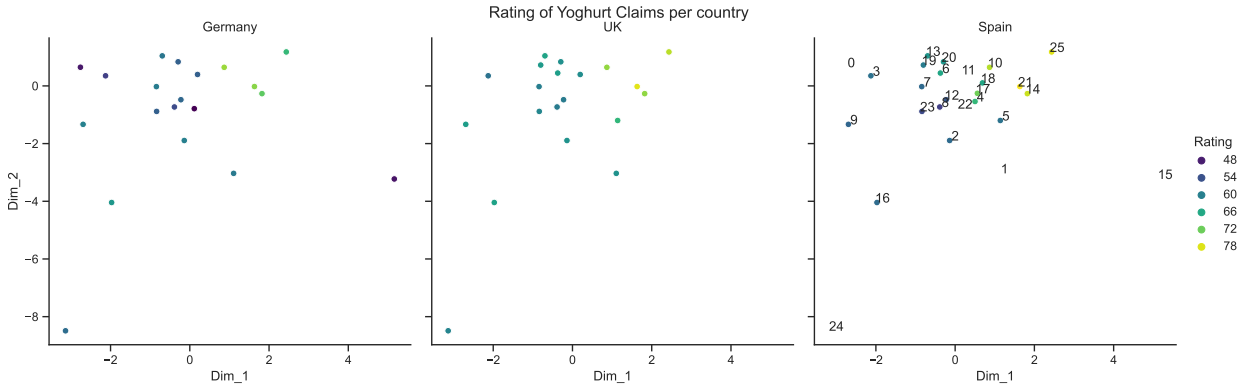
Figure 14: Uniqueness score of embedded yoghurt drink claims.

?@fig-anecdote-mr5 shows the encoding space for the yoghurt drink advertising claims, and illustrates how the embedding picks up on language features of the documents. Namely, Figure 12 colors the claims based on whether they contain the words "taste" or "sense", "natural", and/or "immune system". We color-coded these three by the basic colors (yellow, red, blue), and claims that contain multiple of these words by the mixtures of these colors. If a claim contains none of these words, we code it in grey. These "flag-words" come from looking at the factor space and comparing close advertising claims with each other, through this exploration we discovered these flag-words. Hence, this is not an external label. Claims with the same word features live in similar regions of the encoding space, while claims that contain none of these words, are pushed to the outside of the plot. Intuitively, we would expect that claims which contain multiple of these word features form a transition between the claims which only have one of the word features. For this, we only have claims 13 and 21 as examples, whereas the former does not form such a boundary, and the latter is at the edge of the "Natural" and "Immune System" class. Despite not being an external label, these word features tend to cluster to certain regions in the BERT visualization as well. Similary, Figure 13 colors the advertising claims blue if they are written with a "morning" theme. An example for such a claim would be "*Begin your day with a crisp and revitalizing taste*" (synthetic example, see above). Like the word features in Figure 12, we hand-coded these themes. The split of the two groups is not crisp, but morning themed advertising claims tend to occurr in the south-west of the space, while the other claims are in the north-east. Similarly, for the BERT visualization, morning themed claims occurr mostly in the south-east

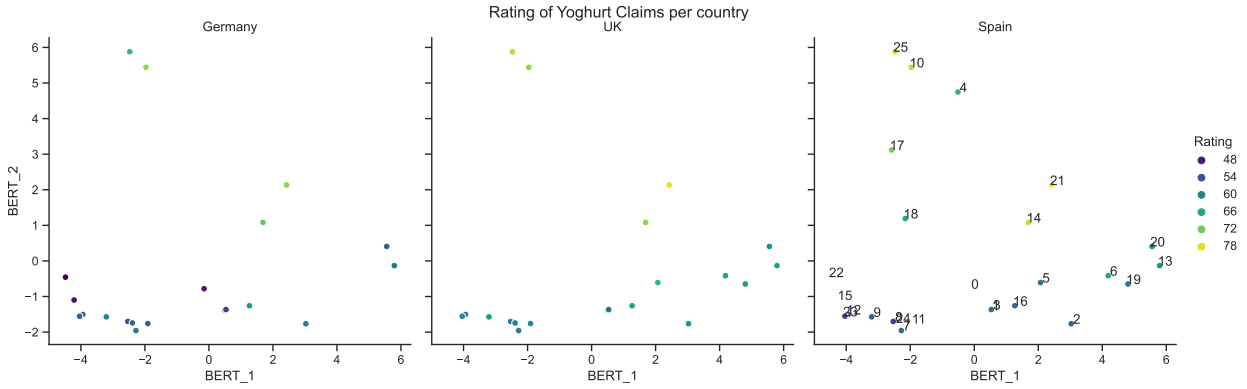
Would be nice if we could assign a numerical score to these things
eg. what is the fit of a MNL (or other classifier) that tries to explain the categories using the 2-dim embeddings as input?

of the plot.

We expect advertising claims that are more unique to have a more isolated position in the encoding space, as they are less similar to other claims. In other words, the uniqueness score should be positively correlated with the euclidean distance of an encoded claim to its neighest neighbor. This is the case for the BERT based space, however, not for our factor space. A potential reason for this could be that two factors are not enough to pick up on higher levels of abstraction, such as uniqueness, while the principal components of a 768 dimensional embedding could. Four the 2-factor summary embedding space, **?@fig-ratings-mr5a** shows that the uniqueness measure and nearest neighbour distance are negatively correlated (−0.4375). In fact, here the three most unique claims (4, 17, 18) cluster together, and the further claims are away from these three, the less unique they tend to be. Claims with low uniqueness scores are spread further apart and far away from the most unique claims. These three most unique claims have some things in common, all of these use a combination of the words "natural", "active", and talk about ingredients (with synonyms). On the other hand, claim 15 is the only claim in the dataset using the word "yoghurt drink" and is also the only claim about emotions. Thereby, it is unique from a language perspective (far away from other points in the encoding), but perhaps not unique to consumers, as there might be similar claims on the market already. Also, uniqueness is highly correlated (0.8843) with the overall rating of claims, some of this correlation could be due to consumers viewing uniqueness as a proxy for "satisfaction". Lastly, the researched advertising claims are self-selected, and perhaps more unique then the average claim that is on the market already. This might lead to a form of Simpson's paradox (Sprenger and Weinberger 2021), where in the population there is a positive correlation between uniqueness and unique language, but perhaps not in this special sub-sample of the data.



(a) Overall rating of embedded yoghurt drink claims.



(b) Overall rating of embedded yoghurt drink claims.

Figure 15: Embedding of the yoghurt claims, colored by word features.

?@fig-ratings-mr5b again shows the encoding space, but this time colored by the overall rating of the

claims and split by the country for which the market was researched. **?@fig-ratings-mr5b** also shows how the same claims can get different ratings by country, the reasons for this could lie in what consumers are used to from the domestic market and in cultural differences. For both the our proposed method and the BERT based visaulization, we find that claims with similar appeal ratings cluster together. For the our document summaries, higher ratings occurr in the north-east and lower ratings towards the south-west of the graph. The clustering of similarly rated claims, could be due to these claims being similar in language. For marketers, there are two insights from this: One, getting the overall theme of a claim right, can ensure that customers perception of this claim is within a certain ballpark. Two, after identifying a fruitful theme for the advertising claim, it is still useful to explore this neighborhood in more fine-grained steps, as locally, there might be small alterations that have large effects on the perception: See e.g. claims 21 (rating in top 4% percentile) and 14 (rating in top 12%), despite one of the shortest distances in the encoding space. When we consider these observations together with the identified word features and themes from above, it appears that advertising claims for yoghurt drinks, which mention the immune system and do not play into a morning theme are appealing to consumers, however these claims are not perceived as the most unique. Claims that mention the word "natural" are among the most unique claims, again not mentioning a morning theme.

Yoghurt-claims and design motivations (Application 2)

For the yoghurt claims, we estimate a 20 factor model and train it until we reach a likelihood of 0.99. We train this model on all unique advertising claims in this dataset. Since we the encoding space is of dimension 20, we cannot use it for visualizations directly. Instead, we apply Principal Component Analysis to these 20 factors, and extract the first two principal components. The intuition behind this is, that if we capture relevant information with these 20 factors, then we might also pick up on this information with the prinicpal components of these factors. As a comparison, we again apply BERT's CLS token to the same advertising claims and perform PCA on the resulting embedding.

As a first step, we are interested in the location of claims that mention a specific country in the princpal component space. These types of claims should have a similar effect on consumers in the domestic market, and hence a good representation of these advertising claims should cluster the different "country-versions" of the same advertising claims together. For this, we flag claims if they mention a specific country and then group these claims into "Claim Types". Some claims don't mention a specifc country but rather a local origin. We collect these claims under the flag "Local". We find three claim types: "Support", "Ingredients", "Origin", and "Made in X". These four claim types are identical in wording and only differ by the mentioned country. The first one is about support for "local" producers, the second one about domestic ingredients, the third one about the origin of the product and the fourth one uses the phrase "made in (country)". In Figure 16 we show the advertising claims in the principal component space and color claims by their mentioned country and adjust the marker type according to the claim type. We collect claims that only occurr once in the claim type "Other". For the BERT embedding, we see that the different claim types cluster together across all groups. For the "Ingredients" and "Made in X" types, the claim from the "Local" location are a bit removed from the cluster. This is plausible, as wording of these claims deviates a bit from that of the respective claims for the nations. We find a similar result for the PCA visualization of our 20-factor model. However, some of the clusters are not as clearly separated from each other (e.g. "Support" & "Origin"). It appears that both types of document summaries capture the information in the texts in such a way, that similar claims cluster together in a two dimensional principal component space.

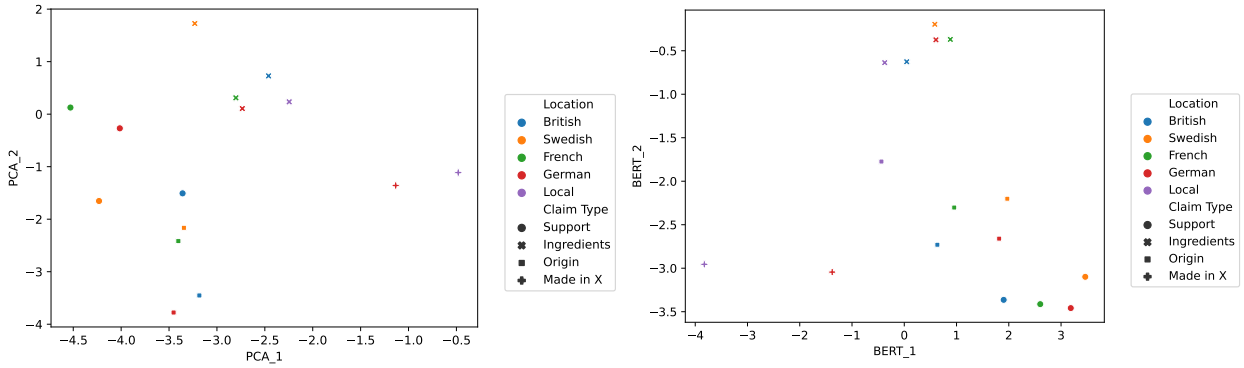
We expand our analysis, by investigating whether we can identify the design motivations of the advertising claims again in a two dimensional principal component space. In Figure 17, we show the first two prinipal components of the generative summary and the BERT summary for all advertising claims from the five major categories "Packaging", "Local & Responsible", "Sourcing", "Naturality", and "Sustainability". In the PCA visualization of the yoghurt claims based on the BERT embeddings, we see that claims with the "Packaging" theme are clearly separated from the other types of claims in the north-west corner of the plot. The claims with the themes of "Local & Responsible", "Sourcing", "Sustainability", and "Naturality" do not seem to exhibit a specifc pattern and are meshed together in the south-west and east areas of the plot. The

These parts become a bit repetitive... you could try to better highlight the thing that you want to show/document

PCA visualization is different for the embeddings based on the 20-factor model. Here, advertising claims with the theme "Naturality" appear to be oriented along the second principal component, while the "Local & Responsible", "Sustainability", and the "Packaging" themes are oriented along the first principal component. It also appears that there is a transition between the "Local & Responsible" and "Packaging" themes along this axis. The theme "Sourcing" appears to be situated at the intersection of "Local & Responsible" and "Naturality." The three "Sourcing" claims, with a first principal component between -4 and -2, and a second principal component between 0 and 2, all have the same phrasing which emphasizes their local origin of the yoghurt. The only difference between these three claims is, that they use a different "country" to describe the origin (e.g. *"Made with 100% French ingredients"*). We observe a similar pattern for the four most south-west "Sourcing" claims, which only differ by an adjective which specifies the origin of the farmers from which the product is sourced. The two most south "Naturaliy" claims, are claims that mention the local and organic ingredients of the yoghurt. This ties in with the surounding claims, which are part of either the "Sourcing" or "Local & Responsible" themes. The two "Packaging" claims, which have a first principal component of smaller than one, emphasize how the packaging is not wasteful, while the most "northern" packaging claim, points to "plant-based" packaging materials. Most of these "Packaing" claims revolve around e.g. recycable or eco-friendly packaging. Hence, it appears fitting that most of the "Sustainability" claims are also located among these claims.

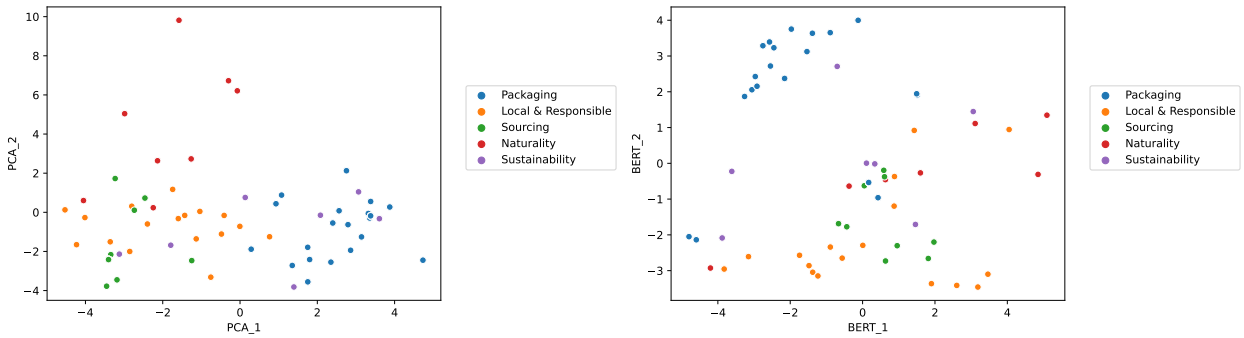
In the word embedding literature, a prominent example to explore the information content of these embeddings is to compare linear combinations of word embeddings to other word embeddings. For example (**mikolovDistributedRepresentationsWords2013?**) present the following example: The word embedding of the word "Queen" is the closest word embedding to the combination of the word embedding for "King", minus the word embedding for "Man", plus the word embedding for "Woman". Here, we try something similar with the advertising claims: We form linear combinations of the summary embeddings and generate a text from the resulting vector. For example, we can alter the country of origin for an advertising claim, as follows: The generative summary for "Yoghurt produced in Sweden" - "Swedish ingredients" + "UK ingredients" generates the text "Yoghurt produced in the UK", which is another advertising claim from the training data. Similarly, in an attempt to generate the claim "Yoghurt produced by local farmer" (which is not part of the training data), we form the combination "Yoghurt produced in Germany" - "German ingredients" + "Local Product", which yields: "Producing farmer Produced by the local farmer [repetition]". While the generated text is not grammatically correct, does not end with an eos-token and contains a repetition, it does seem to capture that we want an advertising claim that emphasizes the local producer of the product, and contains no mention of the ingredients themselves. Finally, we find indications that generated claims make use of associations that the LLM has learned, which go beyond grammatical structures. The combination "Vegetarian ingredients" + "Local production" - "Overpackaging" generates the text "Locally sourced in the United States of America. We are in the process of moving to the United States of America. [repetiton]". While this is not a valid advertising claim, it contains mentions of local production. Perhaps, subtracting the generative summary for "Overpackaging" leads to the generation of "United States of America", which is a country that is never mentioned in the training data, but might be associataed with packaging waste in the pre-training data of the used LLM.

Mention somewhere which LLM we use and what the downsides of that LLM is (repetitions are a common problem I thought in the model that we use)



(a) First two principal components of the 20-factor model (b) First two principal components of the BERT model

Figure 16: Coloring of claims by whether they mention a certain origin country.



(a) First two principal components of the 20-factor model (b) First two principal components of the BERT model

Figure 17: Embedding of the yoghurt claims, colored by word features.

Managerial Implications

perhaps also here: broaden the scope beyond adv claims?

Managers can use ~~these~~ summary embeddings to augment the design process of advertising claims. The work by Burnap, Hauser, and Timoshenko (2023) and Ludwig and Mullainathan (2023) propose a framework for guided generation of images. The researchers model an embedding space for images, that fulfills two requirements: One, points in this embedding space can generate new images and two, they form useful features for a supervised machine learning task. For our setting of text data, we also estimate an embedding that can generate new text data and captures inherent information of the advertising claims, which could be used for classification. The framework which Burnap, Hauser, and Timoshenko (2023) and Ludwig and Mullainathan (2023) use consists of three components: The encoder, which projects datapoints into an encoding space, the generator, which turns points from the encoding space into new datapoints, and the predictor, which predicts a certain label based on a point from the encoding space (compare Burnap, Hauser, and Timoshenko 2023). Burnap, Hauser, and Timoshenko (2023) propose a process to use this generative framework in the design process of cars, by optimizing for the predicted rating of a certain car-design. In a similar way, businesses could use such a setup to improve their advertising claims, e.g. by training the generator and predictor model based on existing market research data. Based on existing market research data which companies have on the performance of advertising claims that they workshopped in the past, we can train a predictor model which predicts a certain outcome measure based on the summary embedding of the advertising claim. We can combine such a predictor model with the low-dimensional factor space of the summary embeddings, to guide the exploration of this space. For this, we only need the decoder part

we can admit that our generated (alternative) claims are not good enough to use directly, but they can still serve as input in a creative process

of our factor model: For every point in the factor space, we can get the corresponding summary embedding and predict the respective outcome for this summary embedding with the predictor model. Through gradient descent, we can now find the point in the factor space that maximizes the predicted outcome. In a classification setting, we can use this technique, e.g. to find the closest point in the factor space which changes the predicted class of the advertising claim.

A framework of generator and predictor model can also help in the design of market research itself. Ludwig and Mullainathan (2023) propose a workflow for generating research hypotheses based on such a model, by finding small steps in the encoding space which maximally change the prediction of the predictor model. They show that these steps yield interpretable and novel hypotheses for their research setting. In a similar vein, marketers might look for the minimal change to an advertising claim, such that this claim changes from being "tangible" to being "intangible". This could help to identify effects of certain design motivations more clearly, as it is closer to the "ceteris paribus" principle, which is difficult to uphold in research designs for modalities such as text.

We show that the distance of advertising claims in the factor space represents their linguistic similarity. Such a measure can be a useful tool when evaluating the market with respect to the positioning of different brands and products. With a visualization similar to **?@fig-ratings-mr5a**, managers can identify which products have similar sounding claims, and make predictions on consumers' ratings of competitors claims, even when they did not incorporate these into their own market research. Such a measure can also help in the identification of copy-cat product claims, which might steal market shares and damage the focal product's brand.

Managers can also explore the factor space to find new design motivations. **?@fig-anecdote-mr5** shows design motivations, which were not designated as themes in the market research study. By looking at the structure of the factor space, and comparing neighbouring claims for the similarities and differences, managers can identify linguistic features, such as the use of certain words of themes.

Do we want to suggest using the embeddings in a conjoint type experiment?

Discussion

In this research, we propose a novel type of document summary, which maximizies the probability to regenerate the focal document. We show that it requires a form of regularization in practice to capture useful features. We also show that these summary embeddings let the generation distribution collapse at the desired target sequence. We can interpolate between two document summaries, and a low-dimensional factor representation captures linguistic similarity of documents. Since this is a new method, further validation is required. Below, we discuss some know limitations and challenges of our document summaries, issues with our applications, and end with next steps in this research.

Limitations

OK!

Newly generated advertising claims are often unintelligible and there appears to be a lot of whitespace in the factor space. We find three reasons for this. One, we use the GPT-2 model in this paper, which is far from the state-of-the-art, e.g. on Huggingface's Open LLM Leaderboard, the best versions of GPT-2 achieve around half the score of the leadboard leader, which is a model based on Llama-3. To address this problem, we can use a more capable open-source LLM, such as Llama 3 instead, which comes at a larger computational costs. The second reason lies in the construction of our factor space. Accoding to Goodfellow, Bengio, and Courville (2016), factor models can learn and represent features of the data well. However, they struggle with generation of new data points, which in practice, tend to be mixtures of the learned features rather than realistic data points. This is a pattern we see with out newly generated advertising claims, e.g. in Table 5. We can address this problem by using a different architecture: Rather than using a factor model, we could use an autoencoder, which takes a different word embedding of the training data, e.g. BERT's `[CLS]` token (Devlin et al. 2018), as an input and learns a mapping from these descriptive embeddings to our summary embeddings. The third reason also related to the architecture

why would we want to bring in BERT as a component? Can't we do without?

non-linear

of our current model, but with respect to the number of layers and activation functions. Currently, we a searching for a representation of the advertising claims in 2 dimensions, and take linear combinations of the resulting factors to create our summary embeddings. Perhaps, this structure is too simplistic to represent this language domain well. Introducing additional layers and non-linear activation functions, such as the Swish function (Ramachandran, Zoph, and Le 2017), might yield to a representation of the space that is better suited for generation, as we learn the manifold on which these advertising claims live, better.

- Linear combinations of generation work, use many more factors than before! Still see similar patterns ...

There are some challenges, which we inherit from LLMs themselves, such as limited language modeling capabilities in non-english languages and safety and copyright issues when generating new text. However, these are problems that we can circumvent, or at least mitigate, by using a more capable LLM with safeguards, or an LLM which has been trained on a specific language if we are working with non-english texts.

We also want to discuss some observations in the computation of these document summaries. The computation time of our factor model depends on two factors. The first one, is the length of the supplied documents, where summaries for longer documents are harder to estimate. The second is the number of factors. Models that have fewer factors get more and more difficult to compute, especially if we are using more and more claims. The intuition for this is, that it gets difficult to "squeeze" many different document through only a few factors, while still regenerating each document. One way how this effects the optimization is, that the log-likelihood plateus and only very slowly increases (if at all). While this might be less of a problem, and more of a statistical fact (we cannot represent certain complexities with a low-dimensional factor model with an arbitrary high likelihood), it can be a issue in certain applications, e.g. when the researcher need a specific (low-dimensional) factor representation for a large number of claims.

could we accept a likelihood well below 1? (assuming that we did find the global max)

Our empirical application has low power and does not allow for generalizations, as it is based on a sample of only 60 observations. Even more so, only have of these 60 observations have a unique claim to them, so our investigations of the claims themselves are only based on 26 observations. Furthermore, we do not make use of the generative capabilities of our document summaries here, which means that such an analysis could also be performed with other methods such as BERT. To validate whether our factor model indeed has regions where claims exist that have e.g. a higher appeal rating, we would need to generate new claims from this region and investigate them in an experiment together with the existing claims.

Expansion of this research

Another adjustments which could improve the quality of our text generation could be to introduce an adversary model, creating an adversarial structure. An adversarial structure consists of two models: A generator and an adversary. The generator creates new datapoints, while the adversary tries to predict whether a datapoint is genuine or has been generated (**goodfellowGenerativeAdversarialNets2014?**). This leads to a game between these two models, where the generator learns to represents the underlying data distribution, such that the adversary cannot distinguish between genuine and generated datapoints anymore. Training such an adversary can also be a way to evaluate the quality of the generated text itself, which is an ongoing research problem (Tatsunori Hashimoto et al. 2019). Exploring how we can reconcile such an adversarial structure with our current training objective of maximizing the generation probability of a focal sequence, is an issue we leave for future research.

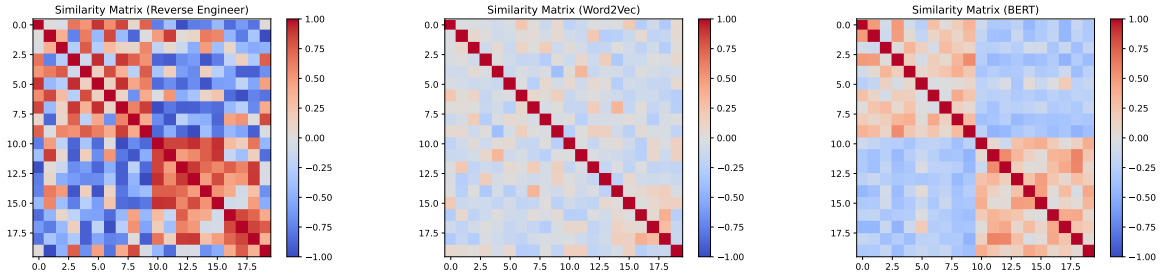
The selection of an adquate number of factors is a hyper-parameter that the researcher most set when using this model. While there can be theoretical motivations for the number of factors (e.g. having two classes as in the test case of intangible and tangible claims), developing a data driven method would be helpful. Such a method could work by penalizing the use of more factors, while rewarding a high likelihood. Perhaps, adapting an information criterion that is based on the likelihood, such as the Bayesian Information Criterion (BIC), could be the starting point for such a development.

Can we adapt the LLM further to a specific domain? For example, the approach by Khattab et al. (2023) also allows for fine-tuning of the LLM with respect to a specifc performance metric. Rather than using an out of the box LLM, which has been trained on large text corpora, we could further train and adapt the LLM to the advertising claims, which are special in their use of words and short. Adapting the LLM to the language domain might prove to helpful, especially when we are interested in the factor space of a specific domain. Furthermore, such an adaptation might also improve the quality of new generated texts, as the LLM pronounces sequences of words that sounds like advertising claims more strongly. Besides fine-tuning, Ouyang et al. (2022) argue that especially Reinforcement Learning for Human Feedback (RL-HF), improves the capabilities of an LLM. Augmenting the training of summary embeddings by RL-HF, in order to regularize the fit of these embeddings by ensuring that they capture signal rather than noise, is another research avenue to purse in the future.

Conclusion

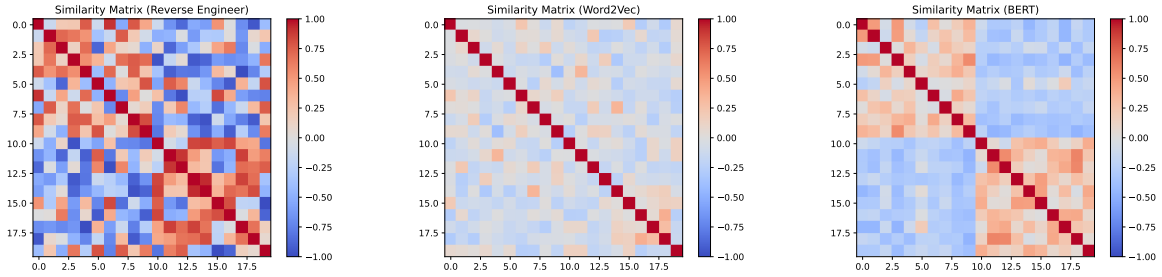
In this research, we propose a novel, optimal, type of document summary, which maximizes the likelihood of an LLM to generate the document that it summarizes. These document summaries are the only ones, which are numeric and can be used for generation of new text. In an application to synthetic advertising claims, we show that these document summaries capture relevant information about the documents, but need a form of regularization to prevent overfitting. We also propose a form of factor model to estimate these document summaries, which yields an interpretable factor space. In an application to market research data, we show that this factor space captures linguistic features and can provide insights on consumer ratings of uniqueness and overall appeal, as well as help with the discovery of design principles. We observe that linguistic uniqueness is not the same as perceived uniqueness by consumers, and that claims of similar appeal ratings cluster together. However, we also observe that small adjustments to the wording of claims can lead to relatively large differences in rating. From this we propose that market research on advertising claims, should consist of two stages, a first stage where the researchers explore the space of claims widely, trying to identify a type of claim with a high appeal ratings. In a second stage, the researchers should then zoom-in on the sub-region and research the effects of fine-adjustments to the wording of claims in this region. Open issues of our approach are to solve the problem of regularization in a more general way, to improve the quality of newly generated text, and to scale this approach to a larger corpus of documents.

Appendix



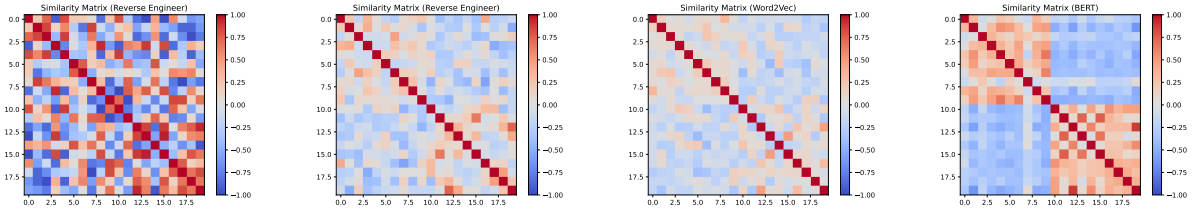
(a) RE (b) W2V (c) BERT

Figure 18: Correlation matrices for the surface cleaner claims.



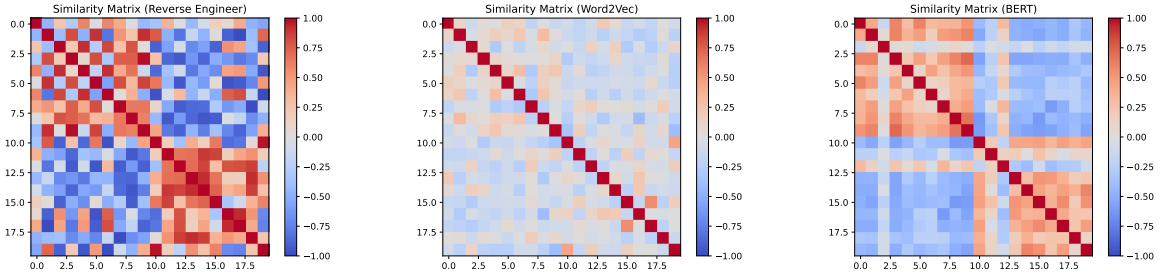
(a) Scrambled order (b) W2V (c) BERT

Figure 19: Correlation matrices for the scrambled surface cleaner claims.



(a) 2-factors (b) 15-factors (c) W2V (d) BERT

Figure 20: Correlation matrices for the hair claims with color attribute.



(a) RE (b) W2V (c) BERT

Figure 21: Correlation matrices for the hair color with health attribute.

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